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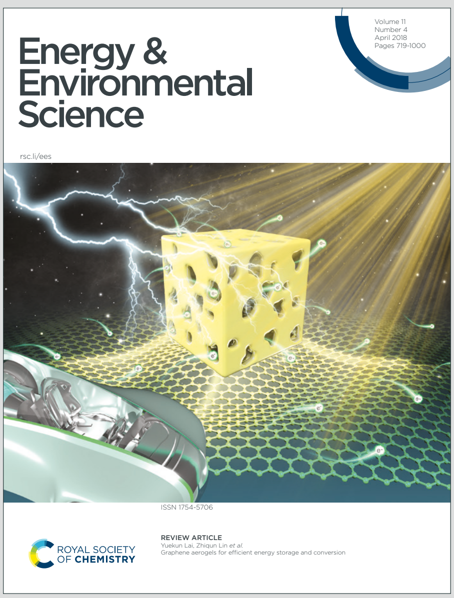

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Broader context

Clean electricity is becoming central to decarbonisation goals, helped by rapidly expanding solar and wind capacity. The highly correlated output from variable renewables depresses power prices, meaning the value of renewable electricity is declining, potentially threatening investment in regions with strong resources and ambitious climate targets. Combining renewables with on-site energy storage is seen as a solution, but its economic viability remains poorly understood. This study asks when, where and how does combining renewables with storage create economic value? By comparing stand-alone, co-located and fully integrated hybrid projects across multiple countries, the results show that storage is not a universal solution. Its value depends on access to multiple markets for revenue stacking, on the ability to charge from the grid, and on high price volatility. Where these conditions align, hybrid systems can stabilise revenues, reduce curtailment, and make better use of limited grid connections. Where they do not, storage risks being underutilised and unprofitable. These findings matter for policymakers designing electricity markets and decarbonisation pathways, and investors allocating capital into projects. By linking market design to project viability, this work helps ensure that storage supports the transition to clean electricity.

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Maximising the economic value of renewable and battery storage hybrids with revenue stacking

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Abstract

As power systems add more wind and solar, electricity supply becomes less controllable and market prices become more volatile. A growing challenge is that renewable generators increasingly earn below-average market prices because their production is highly correlated, an effect known as “revenue cannibalisation” or declining “capture rates”. Co-locating battery storage with renewables is widely proposed to shift output to higher-value hours, reduce curtailment, and share grid-connection infrastructure, but the most profitable configurations remain unclear across markets and regulatory designs. This study asks when renewable-storage hybrid projects are economically superior to stand-alone renewables or storage, and which designs and operating strategies best protect revenues. We develop a revenue-stacking optimisation model with explicit efficiency losses and battery degradation to show that profitability depends more on market access and operating constraints than on location alone. Considering a UK case study, we find storage only becomes strongly profitable when it can both charge from the grid and stack revenues across markets. Four-hour discharge duration was most cost-effective, and stand-alone storage tends to be more profitable than co-located or hybridised systems. Extending the analysis across several world regions shows wide geographic variation. Stand-alone storage is favourable in Australian, Nordic and most US markets, while renewable-storage hybrids are superior in Europe, Texas, and parts of Japan. These results provide a practical map from market design and regulation to profitable hybrid architectures, helping investors and policymakers target storage where it most effectively stabilises renewable revenues and supports reliable decarbonisation.

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1 Introduction

Integrating variable renewable energy sources (RES) is challenging, as existing power systems were designed for dispatchable electricity generators. Variable solar and wind power require flexibility to balance supply and demand [1]. Instantaneous fluctuations in RES output can cause frequency oscillations [2], while seasonal variations in output require longer-term balancing [3,4].

Currently, dispatchable fossil fuel plants provide most flexibility, but these must be displaced by low-carbon alternatives [5]. Although variable generators can provide synthetic inertia and reserve, additional flexibility is needed to maintain system reliability [6]. Location constraints of RES further challenge the grid, as their distributed integration can cause congestion and voltage drops, increasing the need for ancillary services [7,8].

Flexibility includes both demand-side and supply-side measures. Demand-side flexibility, considered practical and cost-effective, involves changing consumer behaviour in response to price fluctuations or incentives [9,10]. Challenges include predicting flexible power availability and designing incentives for end-users [11]. Grid reinforcement can also increase flexibility, for example through interconnections between regions with ‘complementary’ weather patterns [12], yet these require substantial capital and multilateral coordination [13]. Electricity storage provides flexibility by time-shifting production and demand, ideal for integrating RES [14]. Global storage capacity could exceed 600 GW by 2030 with falling costs and diverse applications [15].

Co-locating RES with electricity storage has attracted attention from academia and industry [16], with potential to reduce both curtailment by aligning renewable production with electricity demand and capital costs by sharing inverters and grid connections [17,18]. Co-location can also optimise grid connection capacity, often underutilised in RES-only setups, and accelerate RES deployment by reducing connection requests [19]. This supports on- and off-grid applications, enabling new purchasing contracts with better output timelines [20]. However, regulatory challenges remain and investments must evolve alongside business models [21].

This paper optimises the technical and economic aspects of hybrid RES and storage projects to identify set-ups and operating principles which maximise profitability. It combines a detailed UK case study combining multiple markets with a simpler comparative international analysis. The paper is structured as follows. Section 2 reviews

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related literature, and Section 3 details our methods and model development. Section 4 presents results from a UK case study and international analysis. Section 5 discusses the insights and limitations for decision-makers, and concludes.

2 Background

2.1 Renewable energy and electricity markets

Under marginal-price electricity markets, renewables bid near-zero prices that reflect their short-run marginal cost [22], shifting the merit order and depressing wholesale clearing prices [23]. As variable RES grow, this "merit-order effect" translates into falling technology-specific capture rates (i.e., the ratio of the average price received by RES to the average market price), widely labelled "revenue cannibalisation" [24]. Declining price-weighted revenues, together with curtailment risk, now rival capital cost as the binding constraint on renewable investment [25]. For example, Spain's solar capture rate has fallen by 20% in six years, and is projected to fall a further 15% by 2030 [26–28].

Conventional support mechanisms such as feed-in tariffs or contracts-for-difference insulate producers from market signals and can exacerbate negative-price events by incentivising RES generation irrespective of market prices [29,30]. Newer price-responsive feed-in premiums are emerging [31,32], but these only partially hedge volatility.

Against this backdrop, co-locating low-cost energy storage with generation offers a structural hedge: shifting excess output to high-value periods cushions cannibalised revenues and supplies system flexibility without distorting price formation. Consequently, understanding how hybrid renewable-plus-storage configurations mitigate revenue cannibalisation constitutes the central motivation for the present study.

2.2 Energy storage

Energy storage provides flexibility for integrating variable RES [33]. Technologies differ in power and energy capacity and discharge duration: some are best suited to high-energy applications (e.g., hydrogen and pumped hydro) and others for high-power applications (e.g., capacitors and flywheels) [34,35]. Storage technologies differ significantly in installed capacities and operational characteristics [34]. Pumped hydro remains the dominant technology, but global battery storage capacity is growing rapidly (sixteen-fold between 2016 and 2022) [36].

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The evolving energy landscape presents diverse opportunities for storage technologies, including bulk energy supply, ancillary services, transmission, and end-user applications. Each service requires different discharge durations and response times [34]. Storage systems can increase profitability by stacking multiple services, depending on location and regulations [37,38]. Market conditions are also important; for example, the UK's ancillary services market faced saturation post-2023, pushing operators towards energy arbitrage [39].

Project viability depends on profitability, and thus on costs across the value chain, discount rates, and replacement intervals. Capital costs of most storage technologies fall as installed capacities rise, although some have reached a plateau (e.g., pumped hydro and lead-acid batteries) [34,40].

2.3 Hybridisation

Hybrid renewable energy systems (HRES) combine variable RES with storage through different configurations. HRES could bolster technology deployment and revenues while reducing costs, but revenues depend on location, operation, and installation, all of which should be optimised [41]. Key categories include co-located resources, virtual power plants, and full hybrids. Co-located resources share a grid connection but operate independently, reducing costs through shared infrastructure but limiting value if grid capacity is constrained. Virtual power plants operate separately but coordinate to optimise revenue and support grid management, ideal for markets with limited interconnection sharing. Full hybrid systems are fully integrated, using a single inverter to reduce losses and curtailment, but require complex co-optimisation. HRES can use either AC or DC coupling, each with unique advantages and drawbacks (see Appendix 1) [42–44]. The choice depends on location and project requirements, with AC-coupling dominating but interest in DC setups growing [20].

HRES projects still face patchy or siloed regulation across major markets such as the US, Germany, Spain and the UK, although recent policies are starting to recognise co-located assets. To secure bankable revenues in this evolving landscape, developers are turning to innovative subsidy-free power purchase agreements (PPAs), including capacity, shaped and blended structures, tailored to hybrid operational profiles (see Appendix 2).

2.4 Modelling and optimisation methods

The profitability of HRES viability depends fundamentally on asset sizing and operational strategies, thus optimising HRES has attracted attention from academia and industry.

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HRES are characterised by complex connections among diverse assets. Optimisation is crucial for sizing assets efficiently, with various methods offering distinct advantages and disadvantages [45,46]. Traditional methods use mathematical formulations to find global optima but struggle with high complexity in multi-variable scenarios [47]. Artificial intelligence (AI) mimics human problem-solving and can handle non-linear problems and incomplete data, providing a powerful alternative to traditional methods [46]. Hybrid approaches combine multiple algorithms to improve accuracy and efficiency [48]. Various software tools have been developed to aid in optimising HRES [49].

Optimisation requires an objective function for maximisation or minimisation, with evaluation criteria for HRES divided into reliability, economic, and environmental criteria (see Appendix 3) [46,50]. Most studies prioritise economic or reliability criteria. Common economic indicators include levelised cost of electricity (LCOE), net present value (NPV), and life cycle cost (LCC), while loss of power supply probability (LPSP) is the primary reliability indicator. Economic criteria typically serve as the primary objective in grid-connected projects, while off-grid projects prioritise reliability [51]. Analytical and probabilistic methods are the most widely used, and several studies apply traditional sizing optimisation [47,48,52] (see Appendix 4). Battery storage is frequently assessed, with some studies exploring hydrogen production, particularly for off-grid reliability.

2.5 Summary of gaps in the literature

As HRES configurations continue to develop, further research is needed to evaluate their technical and economic viability and fill seven key gaps in the literature. First, most research has focused on modelling hybrid assets to enhance the reliability of microgrids or remote areas, aiming to reduce diesel generator use [53], whereas relatively few studies have evaluated HRES configurations for utility-scale applications. Second, research has focused on optimising reliability over revenue maximisation. For example, some studies have evaluated load management with energy storage but overlooked economic viability [54]. Third, economic assessments of HRES have used metrics like NPV or LCOE, but focused control strategies on matching electricity output with demand. Storage systems were treated primarily as an excess energy reservoir, neglecting market prices, which influence profitability. Fourth, studies tend to examine wind or solar in a single market and do not compare the profitability of HRES across technologies or markets. Fifth, optimisation studies have mainly developed bidding algorithms for the wholesale market; however, long-term contracts also provide potential revenue sources, meaning that asset sizing and operation should also be optimised across markets. Sixth, the weather-dependent nature of renewables causes regional variations in output, so analysing diverse locations could identify areas more suitable for hybrid assets. Some studies have provided

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regional comparisons but focused on materially similar markets [55]. Finally, many studies have overlooked battery self-discharge and degradation, which could substantially affect asset management.

This paper fills these gaps by optimising the profitability of HRES across diverse markets, accounting for all of the main factors which influence asset management to identify which regions and configurations are preferable for HRES and in what context.

3 Methods

A two-step algorithm was developed to optimise HRES operation and sizing across scenarios. The model was developed in Python and uses Google's OR-Tools optimisation toolkit, specifically GLOP [56], a linear programming solver, to handle the control strategy algorithm. Figure 1 outlines the optimisation workflow of the model.

The first algorithm optimises HRES operations to maximise revenues over a set period using historical data on electricity production, market prices, storage parameters, and renewable energy costs (Appendix 5). The second algorithm applies the same control strategy across different capacities and financial parameters to optimise storage size. Separating the algorithms reduces the computation time and memory requirements.

The optimisation framework detailed in the following sections is first applied to a detailed UK case study which considers various combinations of revenue stacking. It is then used for an international comparison across 30 countries that focuses on arbitrage operation to assess the geographical variability of results. In the UK and international analysis, revenues are modelled under both co-located and fully hybridised setups.

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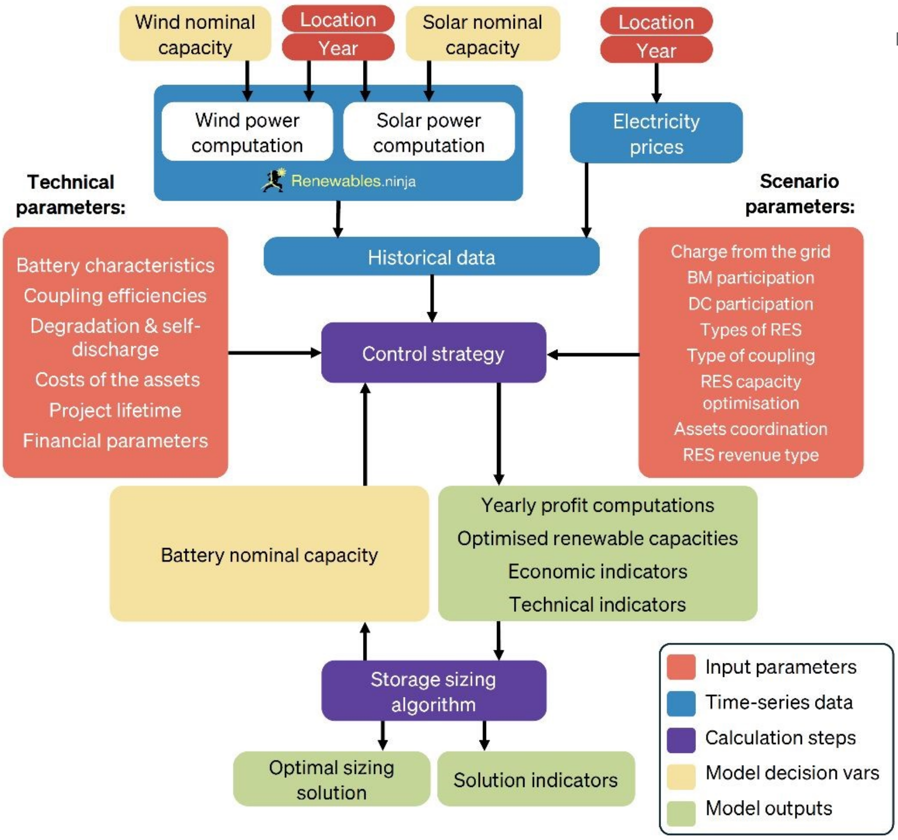

Figure 1: Flow diagram showing the two-step optimisation of control strategy and storage sizing.

3.1 Country and site selection

Our UK case study is based on Lyneham Solar Farm, located in southern England. The site was chosen at random from the MW-scale solar farms operating in the UK (see Appendix 5). Two additional UK sites were modelled to test the sensitivity of results, finding that while annual profits strongly depend on renewable capacity factors (and thus on location), the optimal sizing of storage and other infrastructure did not (see Appendix 12). The UK case study considered revenues from participation across the wholesale, balancing and dynamic containment markets, as price data from these markets are openly available from the system operator.

The analysis is then extended to 30 countries, covering the United States, Europe, Japan and Australia. Countries were selected based on the availability of high-resolution electricity price data, which were required to simulate battery dispatch. Price data were sourced from each market's system operator or market operator (see Appendix 13), and revenues were modelled for wholesale arbitrage only, as data on other markets were not consistently available. Each country within Europe (including the UK) was represented by a single price time series. We considered the five largest sub-national markets in the United States and in Australia, and the eight largest markets in Japan, with each market

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having its own time series of electricity prices. This yielded a total of 45 markets considered in this work.

Markets were then divided into smaller sub-regions to allow for differences in renewable capacity factors to be represented and explored. The number of sub-regions was proportional to the physical size of each market. On average, markets were split into 17 sub-regions in the US, 8 in Australia, and 4 in Europe. Japanese markets cover comparatively small areas and thus were not sub-divided. US power markets were approximated to state boundaries for simplicity. As with the UK case, each sub-region was represented by the site of an existing wind or solar farm, so that results reflect the operation of storage hybridisation at real sites. These farms averaged 198 MW in the US, 194 MW in Australia, 118 MW in Europe, and 32 MW in Japan.

To select the sub-regional sites within each market, the largest wind and solar farms were identified [57], and reduced to a representative set with a weighted max-min version of the p-dispersion algorithm [58]. The minimum distance between all pairs of farms was maximised iteratively, with a penalty function that weights points according to installed power capacity (so that larger farms were more likely to be selected). This approach was chosen to give an even geographic spread within each market, as opposed to (e.g.) *k*-means clustering of sites which would concentrate centroids in specific areas with the most projects. Further details on the process and the sites modelled are given in Appendix 13. Each county within the market was then assigned to its nearest site, so that choropleth maps could be drawn to visualise results. Figure 2 shows the markets covered, how they were subdivided, and the specific sites that were simulated within this study.

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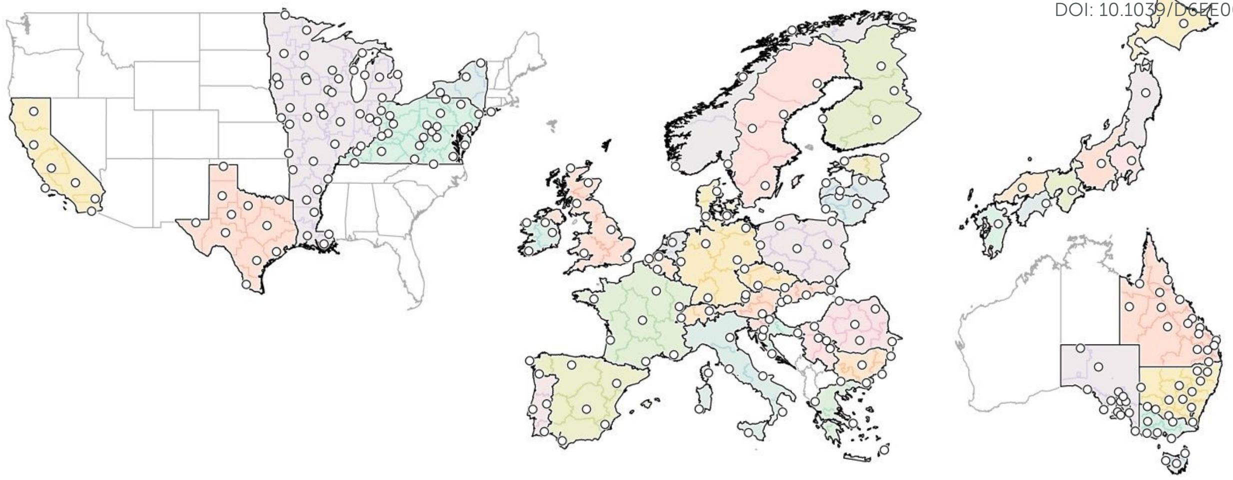

Figure 2: The markets considered in the international analysis across the United States, Europe, Japan and Australia. Across 30 countries, 45 individual power markets are marked by thick black borders, each of which had different time series of electricity prices. Within these, 252 sub-regional zones are marked by thin coloured borders, each of which had different time series of wind and solar production. The site of the wind and solar farm within each sub-national region is marked by a hollow circle.

For each market, wholesale electricity price time series were sourced for the year 2023 from the website of the system operator: CAISO, ERCOT, MISO, PJM, NYISO in the US, ENTSO-E and NESO in Europe, JEPX in Japan, and AEMO in Australia. For each location that was simulated, the hourly time series of wind and solar capacity factors was produced using the Renewables.ninja tool [59,60], based on hourly weather data from 2023.

3.2 Control strategy configuration

Before optimising, the control strategy configures half-hourly parameters derived from historical data, asset characteristics, and costs. Next, scenario variables are initialised to test different configurations. Finally, decision variables are calculated at each time step. Table 1 lists the half-hourly parameters in the model, the project characteristics input into the optimisation, and decision variables for energy flows, grid exchanges, and storage levels. Data collection, sources, processing and values are detailed in Appendix 5.

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Table 1: List of half-hourly parameters, project characteristics provided as inputs, and decision variables in the model. Data collection, sources, processing and values are detailed in Appendix 5.

Symbol	Description	Symbol	Description
Half-hourly parameters			
$SO_{output}(t)$	Normalised solar output profile at the given location (−)	$p_{WS}(t)$	Electricity price on WS market (£/MWh)
$W_{output}(t)$	Normalised wind output profile at the given location (−)	$p_{BM}(t)$	Electricity price on BM market (£/MWh)
$BM_{vol}(t)$	BM volume allocated by the system operator (MWh)	$p_{DChigh}(t)$	Price for DCH reserve (£/MWh)
$DC_{highvol}(t)$	DCH volume allocated by the system operator (MWh)	$p_{DClow}(t)$	Price for DCL reserve (£/MWh)
$DC_{lowvol}(t)$	DCL volume allocated by the system operator (MWh)		
Input Project Characteristics			
η_C	Storage charging efficiency (%)	DoD	Storage depth-of-discharge (%)
η_D	Storage discharging efficiency (%)	SD	Storage self-discharge (%/day)
η_{DC-DC}	DC-DC connection efficiency (%)	Lt_{cal}	Storage calendar lifetime (yrs)
η_{DC-AC}	DC-AC connection efficiency (%)	Lt_{cyc}	Storage cycle lifetime (#)
η_{AC-AC}	AC-AC connection efficiency (%)	cyc_{lim}	Allowed cycles per day (#)
η_{AC-DC}	AC-DC connection efficiency (%)	C_{st}	Storage system CAPEX (£/MW)
ε_{low}	Average proportion of DCL reserve activated (%)	O_{st}	Storage system fixed OPEX (£/MW/yr)
ε_{high}	Average proportion of DCH reserve activated (%)	C_{so}	Solar farm CAPEX (£/MW)
MC_{st}	Charging/discharging variable OPEX (£/MWh)	O_{so}	Solar fixed OPEX (£/MW/yr)
MC_{so}	Solar production variable OPEX (£/MWh)	C_w	Wind farm CAPEX (£/MW)
MC_w	Wind production variable OPEX (£/MWh)	O_w	Wind fixed OPEX (£/MW/yr)
Cap_g	Grid connection capacity (MW)	C_g	Grid connection CAPEX (£/MW)
Cap_{st}	Storage nominal power capacity (MW)	Δt	Time sensitivity of data (hours)
Cap_{so}	Solar nominal power capacity (MW)	T	Number of time steps (#)
Cap_w	Wind nominal power capacity (MW)	N	Project duration (yrs)
T_D	Storage discharge duration (hours)	i	Discount rate of the project (%)
Decision Variables			
$WS_D(t)$	Energy discharged on WS market (MWh)	$W_g(t)$	Energy transferred to the WS market from wind turbines (MWh)
$WS_C(t)$	Energy charged from WS market (MWh)	$DC_{high}(t)$	Reserved energy capacity for charging from DCH market (MWh)
$BM_D(t)$	Energy discharged on BM market (MWh)	$DC_{low}(t)$	Reserved energy capacity for discharging on DCL market (MWh)
$BM_C(t)$	Energy charged from BM market (MWh)	$SOH(t)$	State of health of the storage system (%)
$SO_C(t)$	Energy charged from solar panels (MWh)	$E(t)$	Storage state of charge (%)
$SO_g(t)$	Energy transferred to WS market from solar panels (MWh)	$ageing_{cyc}(t)$	Cycle ageing of the storage system (%/cycle)
$W_C(t)$	Energy charged from wind turbines (MWh)		

3.3 Baseline production and scenarios

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3.3.1 Baseline scenario

The model first runs the baseline scenario, with only solar or wind farms, excluding storage. Solar and wind generation profiles are represented as hourly time series of capacity factors, which are multiplied by installed renewable capacity to obtain power output in each interval. The solar farm exports electricity to the grid if the wholesale (WS) price is positive, curtailing output to avoid exceeding grid capacity (1).

$$SO_g^{ini}(t) = \begin{cases} 0 & if\ p_{RES}(t) < 0 \\ \Delta t * \min(\frac{Cap_g}{\eta_{so-g}},\ \ Cap_{so} * SO_{output}(t)) & otherwise \end{cases} \quad (1)$$

Wind farm production operates like the solar farm but when co-located it adjusts output based on remaining grid capacity after solar dispatches, which has a lower marginal cost (2).

$$W_g^{ini}(t) = \begin{cases} 0 & if\ p_{RES}(t) < 0 \\ \Delta t * \min\left(\frac{Cap_g}{\eta_{w-g}} - \frac{\eta_{so-g}}{\eta_{w-g}} * SO_g^{ini}(t), Cap_w * W_{output}(t)\right) & otherwise \end{cases} \quad (2)$$

Total RES production at the grid connection point $RES_g^{ini}(t)$ combines output from solar and wind and dictates project revenues before adding storage (3).

$$RES_g^{ini}(t) = \eta_{so-g} * SO_g^{ini}(t) + \eta_{w-g} * W_g^{ini}(t) \quad (3)$$

Multiple scenarios are run based on the scenario variables detailed in Appendix 5.

3.3.2 Generation and coupling type

The model can include various asset configurations like stand-alone storage, solar, wind, or hybrid projects (e.g., PV+BESS, Wind+BESS, or PV+Wind+BESS). Variables for excluded assets are set to zero, including nominal power capacities Cap_{so} or Cap_w, and generated energy $SO_g(t)$, $SO_C(t)$, $W_g(t)$ and $W_C(t)$.

Coupling types determine transmission efficiencies between assets and the grid. These efficiencies are detailed in Table 2 and calculations of these efficiencies as a function of the coupling type are shown in Appendix 5.

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Table 2: List of efficiencies defined between the different assets

Symbol	Description
η_{so-g}	Total efficiency from the solar panels output to the grid connection point
η_{so-st}	Total efficiency from the solar panels output to the storage system input
η_{w-g}	Total efficiency from the wind turbines output to the grid connection point
η_{w-st}	Total efficiency from the wind turbines output to the storage system input
η_{g-st}	Total efficiency from the grid connection point to the storage system input
η_{st-g}	Total efficiency from the storage system output to the grid connection point

RES can access various revenue streams, which influences optimisation outcomes. The model incorporates two distinct revenue types: electricity sold directly to the WS market (with prices depending on supply and demand dynamics) and electricity sold via long-term contracts with subsidies or PPAs (with prices fixed over the duration of the contract). For the latter, the $Fixed\_price_{RES}$ variable sets the electricity price obtained by RES, $p_{RES}(t)$ (4).

$$p_{RES}(t) = \begin{cases} p_{WS}(t) & if\ Fixed\_price_{RES} = 0 \\ Fixed\_price_{RES} & otherwise \end{cases} \tag{4}$$

3.3.3 RES capacity optimisation

The model can either fix or optimise RES capacity. For new hybrid setups with storage, where a grid connection permit is secured for the entire setup, the algorithm optimises wind and solar capacities (Cap_{so} and/or Cap_w). For operational assets with fixed renewable and grid connection capacity, the focus is on integrating storage, treating Cap_{so} and/or Cap_w as fixed inputs.

3.3.4 Coordination of the assets

Two asset coordination scenarios are considered. For full hybrids, the assets share a grid connection and coordinate operations to maximise profit, while for co-located resources without joint decisions the RES are assumed to have export priority. The difference lies in the definition of solar, $SO_g(t)$, and wind, $W_g(t)$, energy generated and transferred to the grid.

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For hybrid systems $SO_g(t)$ and $W_g(t)$ are variables but for co-located resources they become parameters corresponding to set according to initial production from Section 3.3.1 (5).

$$\begin{cases} SO_g(t) = SO_g^{ini}(t) \\ W_g(t) = W_g^{ini}(t) \end{cases} \tag{5}$$

The combined electricity output at the grid connection is calculated as:

$$RES_g(t) = \eta_{so-g} * SO_g(t) + \eta_{w-g} * W_g(t) \tag{6}$$

3.3.5 Participation in the balancing mechanism

The storage system can participate in the balancing mechanism (BM) market, initialised with two variables: energy charged (bought) from t to $t + \Delta t$ from the BM market, $BM_C(t)$, and energy discharged (sold) from t to $t + \Delta t$ to the BM market, $BM_D(t)$.

The model considers electricity price, $p_{BM}(t)$, and available volume, $BM_{vol}(t)$, for each interval. Volumes can be negative (drawing energy from the grid) or positive (transferring energy to the grid), determining whether the storage should charge or discharge (7).

$$\begin{array}{ll} \begin{cases} BM_C(t) \leq -BM_{vol}(t) \\ BM_D(t) = 0 \end{cases} & if\ BM_{vol}(t) < 0 \\ \begin{cases} BM_C(t) = 0 \\ \dfrac{BM_D(t)}{\eta_D * \eta_{st-g}} \leq BM_{vol}(t) \end{cases} & if\ BM_{vol}(t) > 0 \\ \begin{cases} BM_C(t) = 0 \\ BM_D(t) = 0 \end{cases} & otherwise \end{array} \tag{7}$$

3.3.6 Participation in dynamic containment

The modelling of dynamic containment (DC) parallels participation in the BM market, initialising additional variables for reserved energy: the energy available at the grid connection point for the system operator, $DC_{low}(t)$, and energy the system operator can provide to storage at the grid connection point, $DC_{high}(t)$.

Unlike the BM market, the DC model distinguishes between dynamic containment low (DCL) and high (DCH). Constraints ensure that reserved energy is within available volume

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for each interval, and if no volume is available, both $DC_{low}(t)$ and $DC_{high}(t)$ are set to zero (8).

$$\begin{cases} DC_{low}(t) \leq \; DC_{lowvol}(t) & if\ DC_{lowvol}(t) > 0 \\ DC_{high}(t) \leq \; DC_{highvol}(t) & if\ DC_{highvol}(t) > 0 \\ DC_{low}(t) = 0 & \\ DC_{high}(t) = 0 & otherwise \end{cases} \tag{8}$$

For each time interval, a proportion of reserved energy is activated by the operator. The activated amount varies but is between fixed proportions derived from historical data, ε_{low} and ε_{high}. Thus, energy transferred through the grid connection is $\varepsilon_{low} * \; DC_{low}(t)$ for DCL and $\varepsilon_{high} * \; DC_{high}(t)$ for DCH. The UK dynamic containment market operates in 4-hour blocks with a fixed price for each 30-minute interval within each block (9).

$$\begin{cases} DC_{low}(i+j) = \; DC_{lowvol}(i) & \forall i \in \{0,8,16,\ldots,N-8\}, \forall j \in \{1,2,\ldots,7\} \\ DC_{high}(i+j) = \; DC_{highvol}(i) & \forall i \in \{0,8,16,\ldots,N-8\}, \forall j \in \{1,2,\ldots,7\} \end{cases} \tag{9}$$

3.3.7 Grid connection configuration

Grid connection configuration determines whether electricity can flow from the grid to the system. With one-way transfer, storage charges only from co-located RES and $WS_C(t)$, $BM_C(t)$, and $DC_{high}(t)$ set to zero. With two-way transfer, storage can charge from the grid and export electricity and $WS_C(t)$, $BM_C(t)$, and $DC_{high}(t)$ are initialised as variables.

3.4 Operation modelling

3.4.1 Capacity restrictions

Renewable assets can transfer output to storage or the grid, but the combined power cannot exceed the nominal capacity during each time interval Δt (10-11).

$$SO_C(t) + \; SO_g(t) \leq \; Cap_{so} * \; SO_{output}(t) * \; \Delta t \tag{10}$$

$$W_C(t) + \; W_g(t) \leq \; Cap_w * \; W_{output}(t) * \; \Delta t \tag{11}$$

Grid connection capacity must not exceed the permitted capacity, Cap_g. This limits maximum bi-directional power transfer during each interval; thus, the sum of all power transactions with the grid must not exceed this capacity (12).

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$$RES_g(t) + \left(WS_D(t) + BM_D(t)\right) * \eta_D * \eta_{st-g} + WS_C(t) + BM_C(t) + DC_{high}(t) + DC_{low}(t) \le Cap_g * \Delta t \tag{12}$$

To represent the total energy through the storage system from t to $t + \Delta t$, a variable $E_{totC-D}(t)$ is computed. For the DC mechanism, $DC_{low}(t)$ and $DC_{high}(t)$ ensure the provision of promised reserves, rather than the actual energy activated by the system operator (13).

$$E_{totC-D}(t) = WS_D(t) + BM_D(t) + \frac{DC_{low}(t)}{\eta_D * \eta_{st-g}} + \eta_{chg} * \left[SO_C(t) * \eta_{so-st} + W_C(t) * \eta_{w-st} + \left(WS_C(t) + BM_C(t) + DC_{high}(t)\right) * \eta_{g-st}\right] \tag{13}$$

The nominal power capacity of storage limits power flow during each interval. This covers charging and discharging, accounting for transmission and storage efficiencies. A constraint ensures that the total power through the storage system $\frac{E_{totC-D}(t)}{\Delta t}$ remains below nominal power capacity, Cap_{st} (14).

$$E_{totC-D}(t) \le Cap_{st} * \Delta t \tag{14}$$

3.4.2 Degradation

The model accounts for storage degradation, which impacts bidding strategy optimisation. Various methods exist [61], but here we follow Hesse et al. [62] and consider two forms of degradation: calendar ageing, $ageing_{cal}(t)$, and cycle ageing, $ageing_{cyc}(t)$. Calendar ageing progresses linearly with time (15) while cycle ageing depends on the number of cycles at each time step (16).

$$ageing_{cal}(t) = t * \frac{\Delta t}{Lt_{cal} * 8760} \tag{15}$$

$$\begin{cases} aging_{cyc}(0) = 0 \\ aging_{cyc}(t) = aging_{cyc}(t-1) + \dfrac{1}{2 * Lt_{cyc} * Cap_{st} * T_D} * E_{totC-D}(t-1) \end{cases} \tag{16}$$

Storage state-of-health $SOH(t)$ is then computed; starting at 1 (100%) and decreasing with the sum of ageing variables (17)

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$$\begin{cases} SOH(0) = 1 \\ SOH(t) = 1 - 0.2 * \left(aging_{cal}(t) + aging_{cyc}(t)\right) \end{cases} \tag{17}$$

Replacement timing is dependent only on calendar life (LT_{cal}), as the endogeneity of including cycle lifetime would substantially increase model complexity. Incorporating cycle-life degradation would make the optimisation path-dependent and non-convex [63], and so less suited for this broad study which required joint sizing and dispatch optimisation across dozens of markets. Based on our inputs of a 13-year calendar lifetime and 4,500-cycle lifetime (see Appendix 5), batteries would reach their calendar lifetime with <0.95 full cycles per day. Our UK case study with the revenue-stacking model sees batteries performing a mean of 1.21 cycles per day, meaning they would fall below 80% SOH after 10.2 years. This would reduce the amount of monetary depreciation that occurs before replacement (as it occurs earlier, it will have a higher present value), but does not change how many stack replacements were required within project lifetime (one replacement after 10 years, rather than one replacement after 13 years). Our international analysis of arbitrage-only operation is less affected, as batteries see a median of 0.96 cycles per day across the 252 locations we model (0.91 median with wind, 0.98 median with solar). This broadly aligns with practical experience, as manufacturer warranties for BESS often allow for a maximum of one cycle per day [34,64], and systems average 0.85 cycles per day in Australia [64], or 1.1 cycles per day in Great Britain (for 2-hour duration) [65].

3.4.3 Daily cycle limit

The model sets a maximum number of daily cycles for two main reasons. Firstly, the model runs only for a single year and therefore considers only short-term degradation, so a daily cycle limit ensures realistic usage patterns are reflected. Second, warranties for storage systems often depend on a specified daily cycle limit. This daily limit is implemented based on daily energy through the storage system, $daily_{C-D}(d)$, which converts the daily cycle limit, cyc_{lim}, into an energy threshold. A constraint ensures that the daily energy transferred remains below this threshold (18).

$$daily_{C-D}(d) = \sum_{k=t}^{t+24} E_{tot\,C-D}(k) \qquad daily_{C-D}(d) \leq 2 * cyc_{lim} * Cap_{st} * \Delta t \tag{18}$$

3.4.4 Energy level

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The model tracks energy stored in the storage system at each time step, $E(t)$, accounting for energy charged and discharged from all sources and markets as well as losses (19).

$$\begin{cases} E(0) = 0 \\ E(t) = \left(1 - \frac{SD * \Delta t}{24}\right) * E(t-1) + \eta_C * \\ [SO_C(t-1) * \eta_{so-st} + W_D(t-1) * \eta_{w-st} \\ + \left(WS_C(t-1) + BM_C(t-1) + \varepsilon_{high} * DC_{high}(t-1)\right) * \eta_{g-st}] \\ - WS_D(t-1) - BM_D(t-1) - \frac{\varepsilon_{low} * DC_{low}(t-1)}{\eta_D * \eta_{st-g}} \end{cases} \quad (19)$$

$E(t)$ must stay within zero and the nominal energy capacity of the storage system, adjusted for state-of-health, $SOH(t)$, and depth-of-discharge, DoD (20).

$$E(t) \leq SOH(t) * DoD * Cap_{st} * T_D \quad (20)$$

To maintain linearity in the model, storage power capacity is constant, separating bidding and sizing optimisations.

3.5 Economic assessment

3.5.1 Costs of assets and electricity purchase

The model includes capital, operational, and replacement costs for the assets. Variable operational costs are proportional to energy output, while fixed operational costs are based on capacity and calculated annually (21).

$$\begin{cases} OPEX_{st}^{var}(t) = E_{totC-D}(t) * MC_{st} \\ OPEX_{so}^{var}(t) = \left(SO_C(t) + SO_g(t)\right) * MC_{so} \\ OPEX_{w}^{var}(t) = \left(W_C(t) + W_g(t)\right) * MC_w \end{cases} \qquad \begin{cases} OPEX_{st}^{fix} = Cap_{st} * O_{st} \\ OPEX_{so}^{fix} = Cap_{so} * O_{so} \\ OPEX_{w}^{fix} = Cap_w * O_w \end{cases} \quad (21)$$

Capital costs are calculated using capacities and are paid at the start of the project. The grid connection cost is proportional to capacity (22). The allocation of this cost among components is detailed in Section 3.6.

$$\begin{cases} CAPEX_{st} = Cap_{st} * C_{st} \\ CAPEX_{so} = Cap_{so} * C_{so} \\ CAPEX_{w} = Cap_{w} * C_{w} \end{cases} \qquad CAPEX_g = Cap_g * C_g \quad (22)$$

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If the lifetime is exceeded, a replacement cost is incurred. We approximate this as 50% of the initial storage system CAPEX, as a simple proxy for future cost of battery units rather than the full system. This is based upon NREL assumptions that replacement cost equals 80% of the battery system's overnight capital cost [66], and projections that battery costs will fall by 30% over the storage lifetime used here [67]. Taken together, these imply a replacement cost of around one-half of present-day cost, which we discount to present value (23), where i is the annual discount rate.

$$CAPEX_{st}^{rep} = 0.5 * CAPEX_{st} * \frac{1}{(1+i)^{Lt_{cal}}} \tag{23}$$

Capital costs are annualised using an annuity factor AF for a given project duration, N, and discount rate, i (24).

$$AF = \frac{i * (1+i)^N}{(1+i)^N - 1} \tag{24}$$

Finally, electricity purchase from WS or BM markets is calculated (25).

$$Cost(t) = WS_C(t) * p_{WS}(t) + BM_C(t) * p_{BM}(t) \tag{25}$$

3.5.2 Revenues

Different revenue streams are considered for the baseline and storage-integrated scenarios. For the baseline scenario without a storage system, revenues are calculated using (26).

$$Rev_{ini}(t) = RES_g^{ini}(t) * p_{WS}(t) \tag{26}$$

When storage is integrated, revenues include the sale of electricity from RES and discharged from storage, and DC revenues based on reserve DC capacity (27).

$$\begin{aligned} Rev_{opti}(t) &= \eta_D * \eta_{st-g} * \left(WS_D(t) * p_{WS}(t) + BM_D(t) * p_{BM}(t)\right) \\ &+ RES_g(t) * p_{RES}(t) + \left(DC_{low}(t) * p_{DC_{low}(t)} + DC_{high}(t) * p_{DC_{high}(t)}\right) \end{aligned} \tag{27}$$

3.6 Objective function and indicators computation

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3.6.1 Co-located resources and full hybrid scenarios

For co-located assets, where renewables have export priority, the aim is to maximise profits for the storage developer. The objective function sums the differences between revenues and costs to yield profits over the period, T. Initial RES revenues are subtracted to consider only revenues for the storage developer, and grid connection costs are allocated between assets based on capacities (28).

$$\begin{cases} Profit(t) = Rev_{opti}(t) - Rev_{ini}(t) - Cost(t) - OPEX_{st}^{var}(t) \\ OPEX_{tot}^{fix} = OPEX_{st}^{fix} \\ CAPEX_{tot} = CAPEX_{st} + CAPEX_{st}^{rep} + \dfrac{Cap_{st}}{Cap_{st} + Cap_{so} + Cap_{w}} * CAPEX_{g} \end{cases} \tag{28}$$

For hybrid systems, RES and storage coordinate to maximise combined profits, and so the objective function is adjusted. Initial revenues from RES, $Rev_{ini}(t)$, are no longer subtracted since assets are jointly optimised and capital and operational costs include all assets (29).

$$\begin{cases} Profit(t) = Rev_{opti}(t) - Cost(t) - OPEX_{st}^{var}(t) - OPEX_{so}^{var}(t) - OPEX_{w}^{var}(t) \\ OPEX_{tot}^{fix} = OPEX_{st}^{fix} + OPEX_{so}^{fix} + OPEX_{w}^{fix} \\ CAPEX_{tot} = CAPEX_{st} + CAPEX_{st}^{rep} + CAPEX_{so} + CAPEX_{w} + CAPEX_{g} \end{cases} \tag{29}$$

In both cases, the objective function to be maximised can be expressed as in (30).

$$f = \sum_{t \in T} \big(Profit(t)\big) - OPEX_{tot}^{fix} - AF * CAPEX_{tot} \tag{30}$$

3.6.2 Indicators computation

After optimising the control strategy, several indicators are calculated alongside profits to be compared across scenarios. Key economic indicators include NPV, internal rate of return (IRR), and payback period (PBP), which are detailed in Appendix 6. Constant annual revenues are assumed across the project's duration, N, adjusted according to discount rate, i. Capture rates are computed for the baseline and optimised scenarios to evaluate the impact of storage on RES revenues (31–32).

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$$p_{captured}^{ini} = \frac{\sum_{t=0}^{T} RES_g^{ini}(t) * p_{RES}(t)}{\sum_{t=0}^{T} RES_g^{ini}(t)} \quad Initial\ capture\ rate = \frac{p_{captured}^{ini}}{\overline{p_{WS}}} \tag{31}$$

$$p_{captured}^{opti} = \frac{\sum_{t=0}^{T} RES_g(t) * p_{RES}(t)}{\sum_{t\in T} RES_g(t)} \quad Optimised\ capture\ rate = \frac{p_{captured}^{opti}}{\overline{p_{WS}}} \tag{32}$$

The proportion of grid connection capacity utilised over time is calculated with and without storage. In the baseline scenario, grid usage is the electricity output from RES at the grid connection point divided by its capacity (33).

$$Grid_{usage}^{ini} = \frac{\sum_{t=0}^{T} RES_g^{ini}(t)}{T * Cap_g * \Delta t} \tag{33}$$

In the optimisation scenario, we consider bi-directional power flow with the grid to account for RES output and the charging and discharging of storage (34).

$$Grid_{usage}^{opti} = \frac{\sum_{t=0}^{T} \Big(\big(RES_g(t) + (WS_D(t) + BM_D(t)\big) * \eta_D * \eta_{st-g}) + WS_C(t) + BM_C(t) + \epsilon_{low} * DC_{low}(t) + \epsilon_{high} * DC_{high}(t) \Big)}{T * Cap_g * \Delta t} \tag{34}$$

3.7 Storage sizing algorithm

The storage sizing algorithm determines optimal power capacity for a given configuration once the control strategy algorithm has provided optimised renewable capacities, profits, and other relevant indicators. The algorithm sets lower and upper bounds for storage capacity and, given the convex nature of the objective function, quickly identifies the optimal capacity. Two methods were compared for the optimisation: the Golden Search method and the Dichotomy method [68]. The Dichotomy method was chosen as it solved faster by splitting the search interval in half and evaluating the function around the midpoint. Appendix 7 provides an example of an optimisation and compares the two methods.

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3.8 Limitations

The model provides a useful approximation of project revenues, but relies on six simplifications. First, electricity prices and RES production data for 2023 were used for each year of the project's lifespan; however, inter-annual fluctuations in prices and output will change outcomes. Future work could use multiple years of historical data or forecasts and assess their impact on optimal configuration and profits. Figure 3 shows how the optimal storage capacity and the NPV of storage installations change with electricity prices. For example, if electricity prices from 2022 are considered, when prices spiked following the Russian invasion of Ukraine, the optimal storage capacity would remain similar but the NPV of the project would be much higher. In contrast, if the much lower electricity prices from 2020 are considered, both the optimal storage capacity and NPV would be greatly reduced compared with the 2022 case.

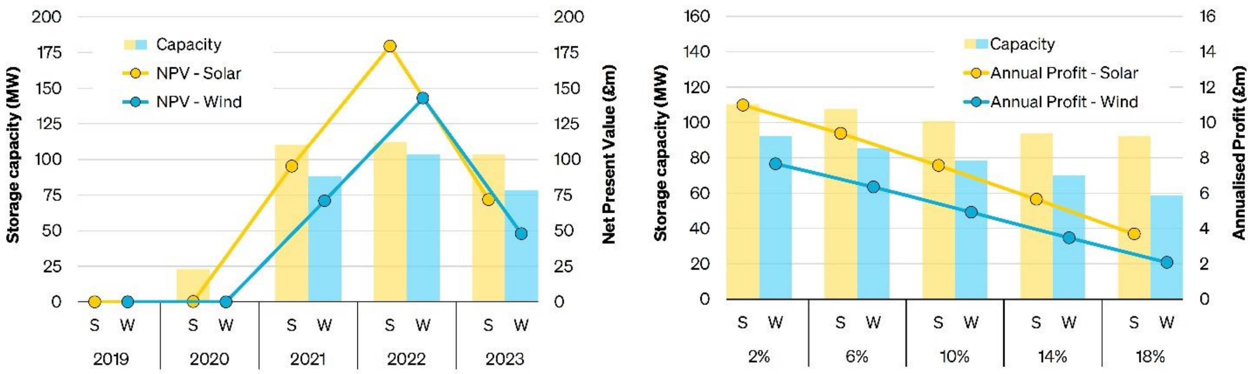

Figure 3: A case study showing the sensitivity of the optimal storage capacity and profit of co-located projects to interannual variations in electricity prices (left), and varying discount rates (right).

Second, discount rates were held constant across all simulations, though they vary by project, country, and over time. Figure 3 shows that optimal capacity and profit decrease as discount rates (i.e., the cost of capital) increase, because overall project costs increase and activities that were marginally profitable with low discount rates turn into losses with higher rates.

Third, storage efficiency and degradation were simplified. Average efficiencies were assumed, although they vary with power output and other operating conditions. Cycle degradation was calculated to be proportional to total energy exchanged when tracking state-of-health, but in practice it worsens with deeper discharge and temperature, among other factors. Only the calendar lifetime was used when calculating the interval between battery replacements, meaning that our model would underestimate the financial impact

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of degradation if batteries were more intensively cycled. Assuming a fixed interval for battery lifetime and replacement is common in techno-economic and market optimisation studies of batteries [69–71], but future work could more accurately evaluate the trade-off of increased utilisation by incorporating cycle life in the replacement interval.

Fourth, the model assumed energy could be exchanged at the clearing price up to the market-determined volume. In reality, energy transfers depend on successful bidding, meaning storage may not always receive the desired volume or clearing price. Incorporating real bid prices and acceptance probabilities would improve the model's accuracy, but these data are proprietary and so cannot be utilised without external co-operation.

Fifth, technologies generally improve and become cheaper over time. Innovation, cumulative deployment, policies, and regulations influence technology and grid connection costs, market dynamics, and the financial viability of projects. This study considers the present case but future work could consider how optimal configurations could change in the future.

Finally, the model assumed curtailment only when renewable output exceeded grid connection capacity. In reality, grid operators may impose additional constraints due to congestion or maintenance, which would reduce revenues and profits.

4 Results

We begin with results from a case study in Great Britain, which focuses on the Lyneham Solar Farm site (Appendix 5) and examines two types of hybrid systems: co-located projects and full hybrid projects. It first assesses the impact of revenue stacking on the profitability of co-located RES-storage projects and considers the optimal storage capacity in different contexts. It then reports a similar analysis for full hybrid projects at existing RES sites, and compares this with co-located systems. Third, it determines the optimal configuration of RES and storage for newly built hybrid systems and shows how profits and the optimal configuration depend upon how electricity is sold (i.e., at market prices or via PPAs). The UK case study is then extended to markets across Europe, the United States and Australia (listed in Appendix 13) using country-specific RES profiles and wholesale prices to assess wider hybrid RES-storage potential.

4.1 Co-located projects in Britain

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Here we assume that a 100 MW wind or solar farm has been constructed with a 100 MW grid connection permit. A developer wishes to add a storage system to exploit cost synergies and reduce permitting time. The assets are located on the same site, but operate independently from the storage developer's perspective.

4.1.1 Profitability across markets

This section focuses on solar, but analogous results for wind are provided in Appendix 8-10, which show broadly similar trends. Storage can charge from the grid and participate in multiple markets, including WS, BM, and DC. Figure 4a compares annual revenues of a 1-hour, 100 MW battery participating across markets and against stand-alone systems. For co-located projects, the solar (or wind) asset takes priority over the BESS when dispatching electricity, meaning that the BESS cannot fully utilise the grid connection. The greatest opportunities for co-location exist where grid connections are under- or over-built, benefitting from either spare grid connection capacity to optimise operations without paying for the grid connection or free electricity from the co-located generator that would otherwise be curtailed. In this case, the grid connection is sized to the same capacity as the solar asset; thus, there is limited spare capacity and no curtailment, meaning that the BESS is underutilised and a stand-alone BESS with its own grid connection would be more profitable. For the co-located BESS, revenues are highest when participating across all markets, and considerably higher when storage can charge from the grid as well as the co-located RES.

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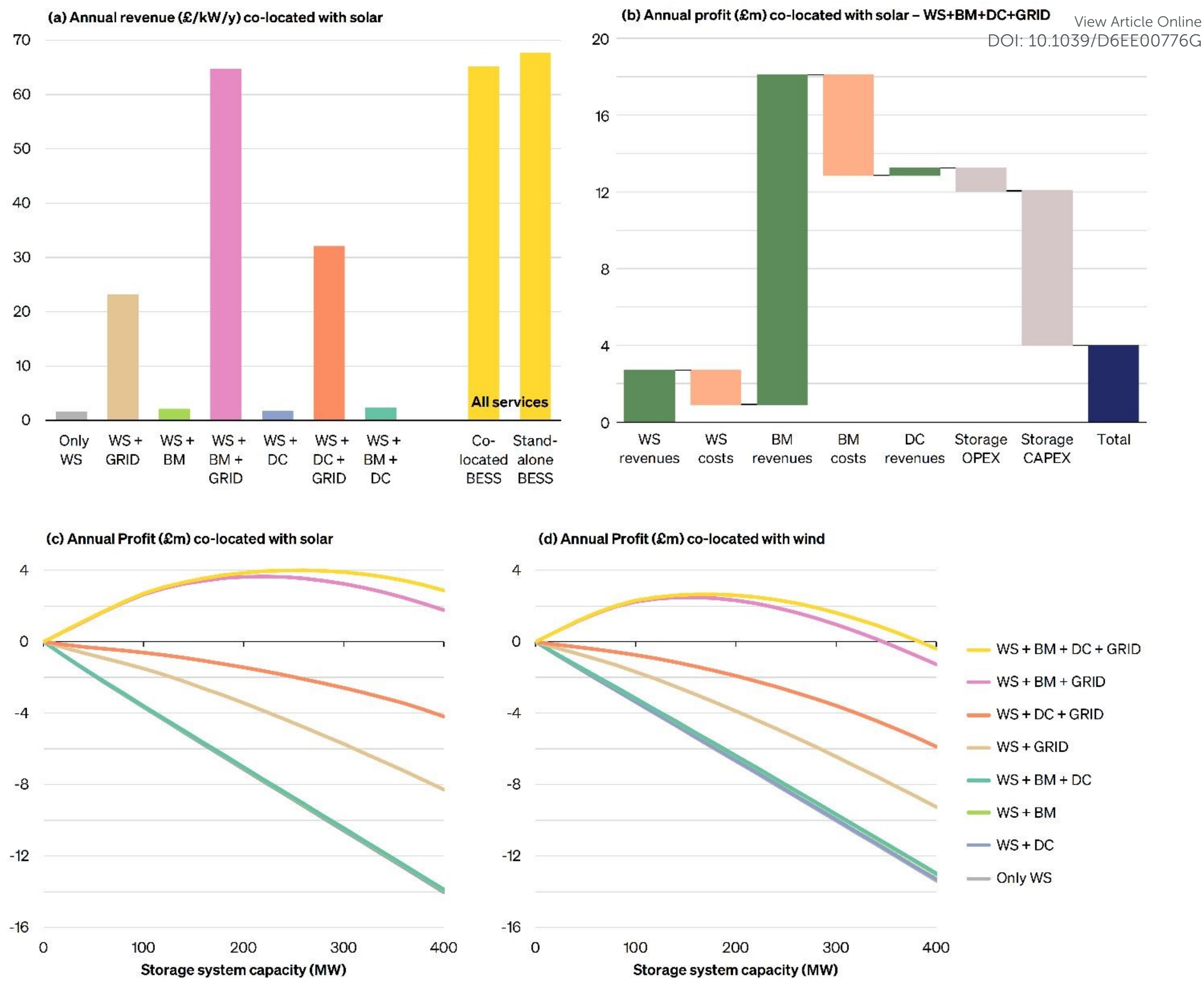

Figure 4 : Annual revenue and profit from co-located and stand-alone energy storage in the UK. (a) Comparison of revenue for different combinations of market participation. (b) Breakdown of revenues (from discharging) and costs (from charging) from each market for the optimal storage capacity co-located with solar providing all services. (c–d) Profit as a function of storage capacity for each combination of markets for storage co-located with solar (c) and with wind (d).

A breakdown of costs and revenues is given in Figure 4b. An annual profit of £4 million is realised, with most profit generated from the BM market. Subsequent simulations are based on the optimal scenario with full market participation and grid charging. Figure 4c compares annual profits for 1-hour storage with different capacities, co-located with the solar farm. Only two scenarios are profitable, both requiring grid charging and participation in BM and WS markets. Participation in the DC market marginally increases profits. When storage participates in all markets with grid charging, the optimal capacity is 252 MW. Figure 4d shows similar results when storage is co-located with the wind farm, albeit with slightly lower profits in all cases.

4.1.2 Impact of discharge duration

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Longer durations of storage increase energy capacity but also costs. Figure 5 shows annual profits for various discharge durations and storage capacities. The range of profitable capacities narrows as discharge duration increases, with highest profits at lower capacities for longer durations. A 106 MW system with 4-hour duration yields the highest profit (£8.5 million), offsetting higher capital cost compared to shorter durations with greater revenues across markets.

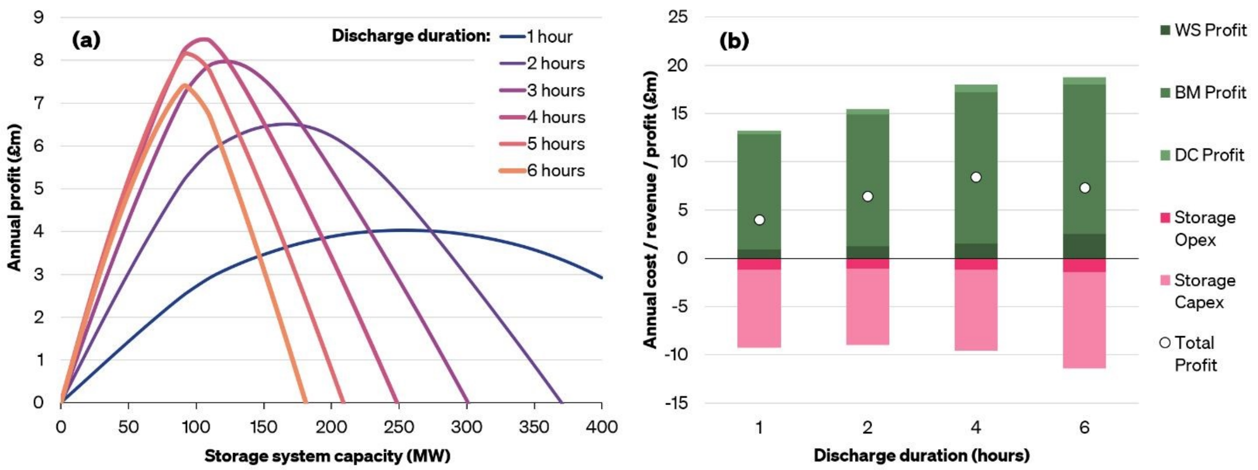

Figure 5: Annual revenues, costs and profits for storage with varying discharge durations. (left) Profits at varying discharge durations and capacities and (right) a breakdown of annual profits by revenues from each market and annualised capital and operating costs for the optimal capacity for each discharge duration.

4.1.3 Impact of RES capacity on optimal storage sizing

Renewable developers can oversize or undersize RES capacity relative to grid connection, either for profit maximisation or future expansion. This section optimises RES-to-grid connection capacity ratio to maximise the value of storage for a common 1-hour system assuming a 100 MW grid connection. We assume that farms are economically viable prior to co-location, so we first identified RES capacities yielding a positive NPV for stand-alone farms (<170 MW for solar and <440 MW for wind). These set the upper limit for RES-to-grid connection ratios.

Figure 6 shows the optimal storage capacity and corresponding NPV of storage systems for different RES-to-grid connection ratios (solar and wind) from 0-2 (solar) and 0-4 (wind), where 0 indicates stand-alone storage. For both solar and wind in the UK, a stand-alone storage system achieves the highest NPV, as full use of the grid connection capacity

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allows BESS dispatch to be prioritised and operations to be optimised, generating greater additional revenues than the costs saved by avoiding the installation of a new grid connection.

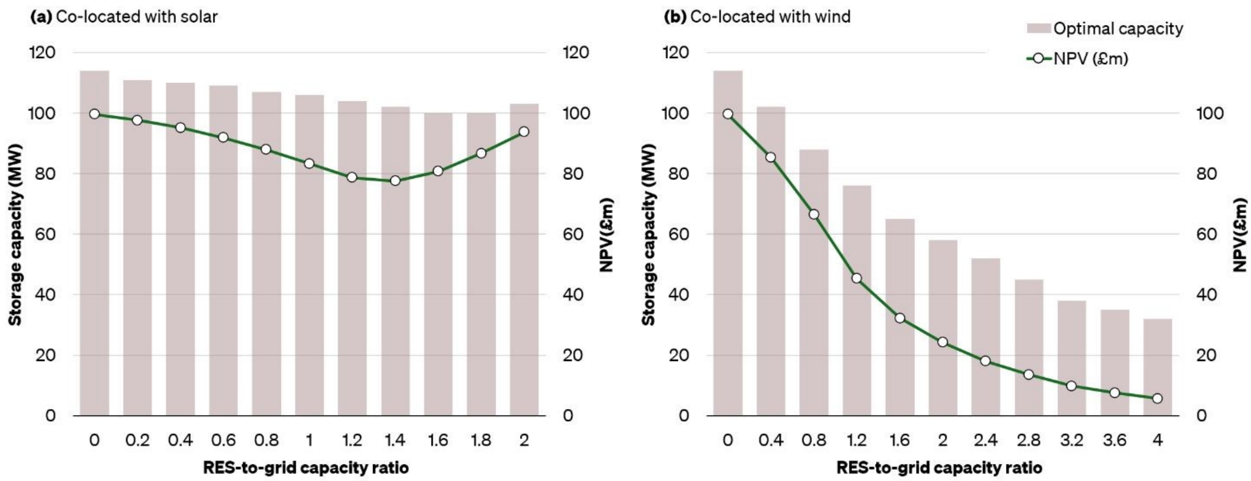

Figure 6: Optimal storage capacity and corresponding NPV for storage and co-located (a) wind and (b) solar farms at varying RES-to-grid connection ratios. An RES-to-grid connection ratio of 0 indicates a stand-alone storage system.

For storage co-located with solar, NPV is greatest with high or low RES-to-grid ratios and optimal storage capacity is between 100-115 MW. For wind, both NPV and optimal storage capacity fall as the RES-to-grid ratio increases. This difference arises from variations in patterns of solar and wind energy. For BESS co-located with solar, the grid connection is fully available to the BESS at night when there is no solar generation. With large overbuilt solar capacity and a high RES-to-grid ratio, the BESS is able to charge using cheap or free surplus electricity during the day and discharge it to the grid for a profit at night. While this improves the profitability of the BESS, a stand-alone system remains the most profitable option even when the RES-to-grid ratio is 2. For BESS co-located with wind, the BESS will never be profitable, even at an RES-to-grid ratio of 4, because higher wind capacity leads to more congestion in the grid connection, further limiting BESS dispatch.

Figure 7 shows the power output and storage operations over a representative 5-day period for solar and wind, assuming an RES-to-grid connection ratio of 2. Appendix 10 shows energy transfers between storage and the grid for other RES-to-grid connection ratios. Storage benefits from the daily cyclic output of solar, storing excess energy during peak production and discharging it when prices are higher, typically in the evening, and can recharge from the grid overnight. In contrast, the wind farm has more consistent output near grid connection capacity, limiting storage utilisation, and long periods of curtailment risk causing self-discharge as there is no spare capacity for storage to discharge.

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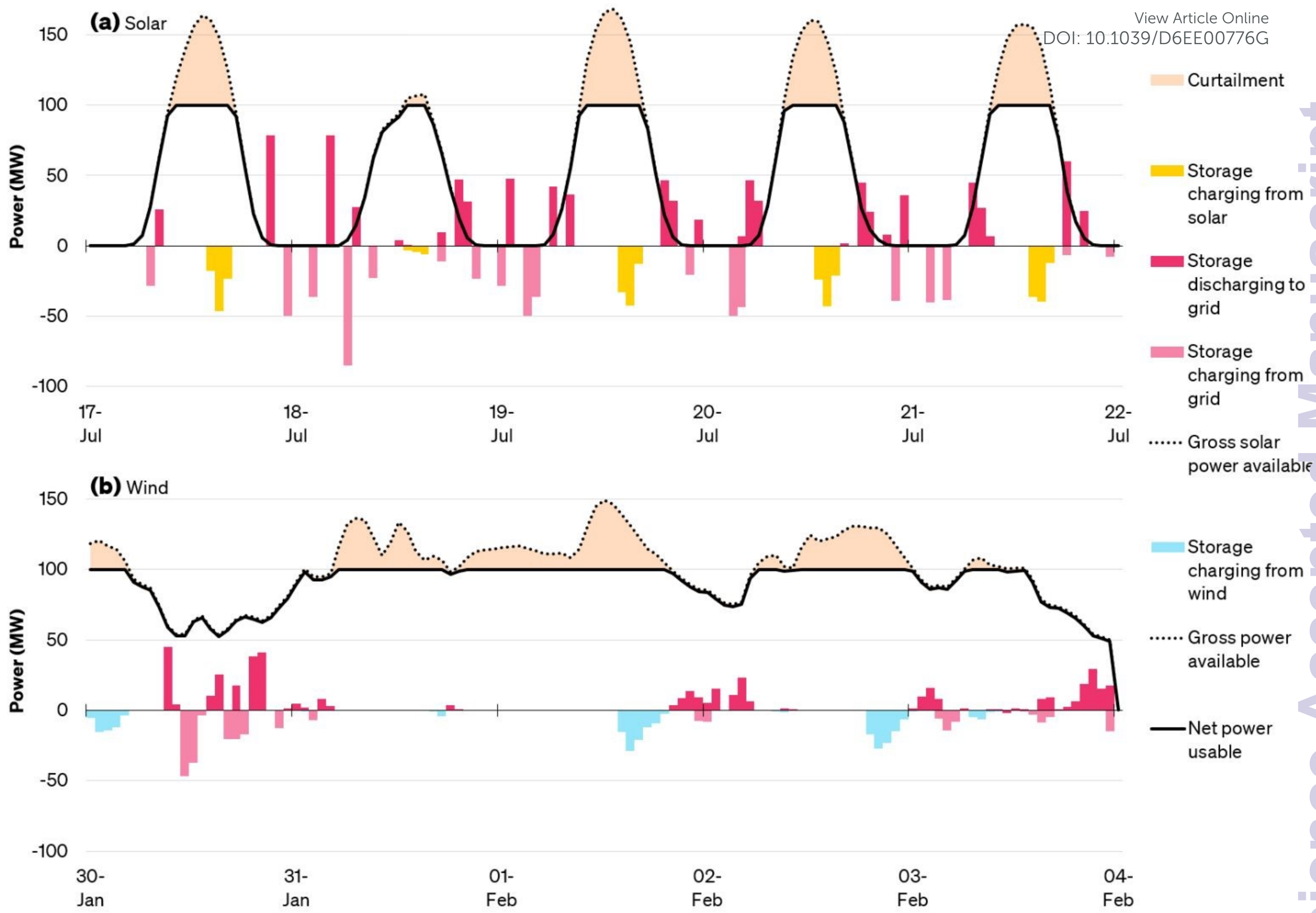

Figure 7: Hourly RES output and storage operations for co-located systems over a representative 5-day period in summer for solar and winter for wind. (a) Solar farm during a summer week and (b) wind farm for a winter week.

4.2 Full hybridisation of existing RES in Britain

Full hybrid projects integrate RES and storage and coordinate operations. This section illustrates how hybrid configurations can be optimised to maximise overall profits, again assuming a fixed 100 MW grid connection.

Figure 8a shows combined profits from 100 MW solar farm hybridised with 1-hour storage operating across markets, compared to those of a stand-alone solar farm. As with co-location, hybrid storage systems must participate in WS and BM markets and charge from the grid for economic viability; however, annual profits are higher for hybrid systems across all storage capacities. Results are similar for wind projects (see Appendix 11).

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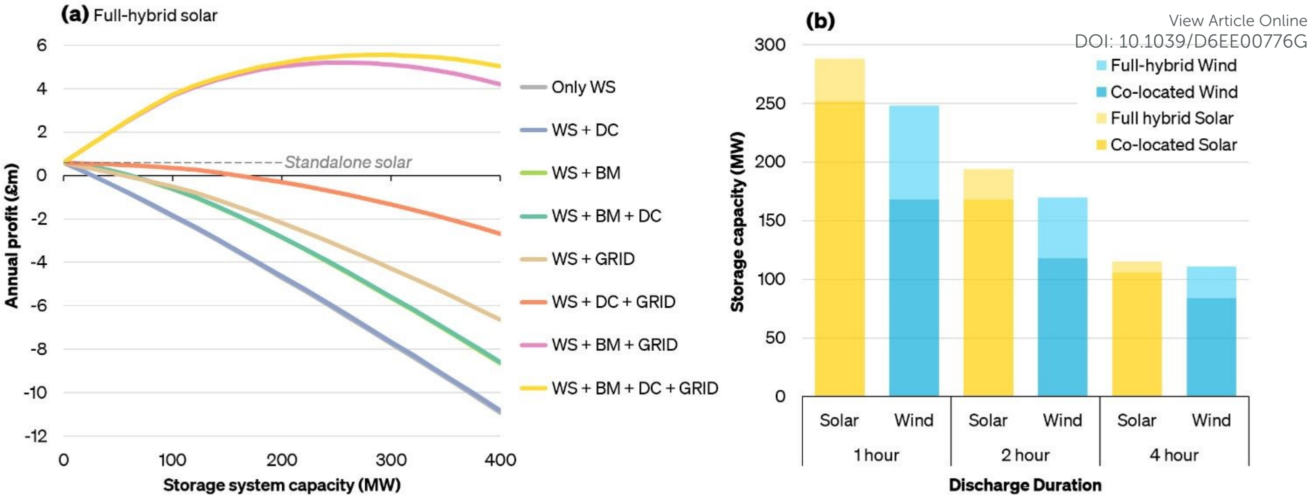

Figure 8: (a) Combined annual profits from power production and storage operations for a fully hybridised solar-storage project when participating in various combinations of markets. Note the dashed line shows profits from the stand-alone solar system. (b) Optimal storage capacities for co-located and fully hybridised storage at 100 MW wind and solar projects.

Figure 8b shows the difference in optimal storage capacities between full hybrid and co-located systems. Full hybrid projects can trade freely with the grid as their dispatch is not de-prioritised as it is in co-located systems. Therefore, the developer sizes the BESS to minimise curtailment and maximise profits from arbitrage, which generally requires greater capacity than in co-located systems where BESS capacity is sized based on the availability of grid connection capacity.

Figure 9 shows the operational patterns of a 200 MW solar farm with the optimal storage capacity of 288 MW over a representative 5-day period. Compared with co-location, full hybrid systems transfer more energy from RES to the storage system, as shown in Table 3, primarily to exploit periods of higher prices by time-shifting output shifting output.

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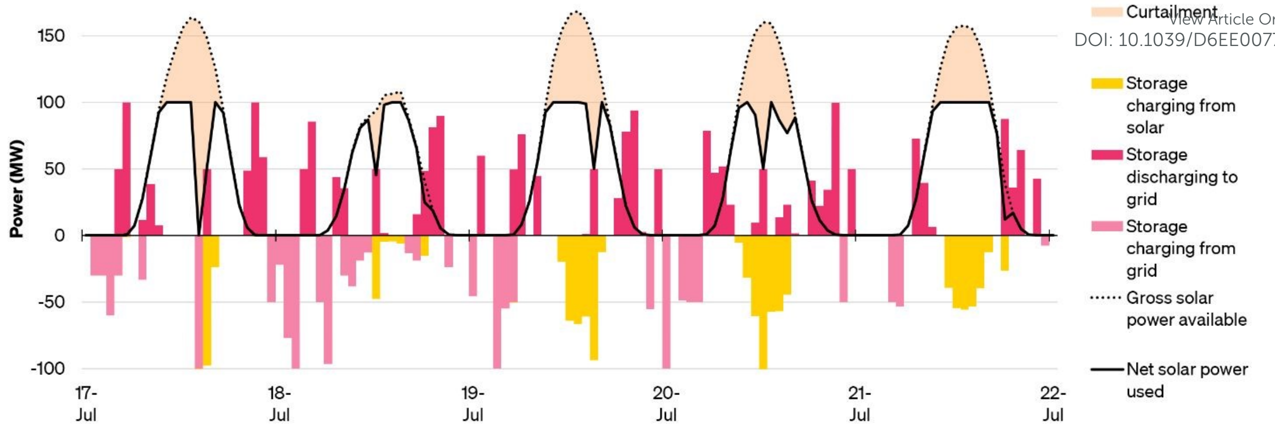

Figure 9: Hourly operation of a fully hybridised project with a 200 MW solar farm and an optimal 288 MW storage system over a representative 5-day period in summer.

Table 3: Yearly energy transferred from solar to storage systems for different discharge durations and the two types of projects (Co-located storage is charged during negative price periods).

Discharge Duration	Co-located	Full Hybrids
1 hr	74.9 MWh	18001.5 MWh
2 hrs	532.0 MWh	30008.1 MWh
4 hrs	30603.8 MWh	37496.2 MWh

The aim of hybridisation is to improve profitability of RES by integrating storage; hence, returns on a hybrid system should exceed those of stand-alone RES. Table 4 compares economic indicators for stand-alone 100 MW wind and solar farms and the optimally sized stand-alone storage system to optimal hybrid configurations. Appendix 12 shows how these results differ depending upon asset location, modelling two alternative sites in the South and North. Incorporating storage improves all economic indicators, increasing RES capture rates and grid connection utilisation; yet, this depends fundamentally on the storage being able to participate in all markets and stack revenues. From the perspective of a storage developer, if a grid connection can be obtained, a stand-alone storage system delivers the highest returns.

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Table 4: Optimal indicators for a full hybrid project with a 100 MW renewable farm. In each case, we assume a 100 MW grid connection and that storage participates in all markets and can charge from the grid.

	Stand-alone wind	Stand-alone solar	Stand-alone storage	Full hybrid solar	Full hybrid wind
Duration	-	-	4 hrs	4 hrs	4 hrs
Capacity	-	-	114 MW	115 MW	111 MW
IRR	8.88%	17.95%	24.31 %	16.31 %	19.50 %
NPV	£5.8m	£107.6m	£99.6m	£103.1m	£185.1m
PBP	15	7	5	8	6
Cap. rate	93.7%	96.4%	-	97.2 %	100.5%
Grid Usage	14.9%	35.3%	53.8%	61.7 %	71.1%

4.3 Full hybrid systems with co-optimisation of RES and storage

When full hybrid systems are built from scratch, developers can optimise both RES and storage to maximise revenues for a given grid connection, again assumed to be 100 MW here. This section considers three potential revenue models for newly built full hybrid systems in the British case study. The first assumes both assets sell electricity directly to markets. The second assumes that RES secures a fixed price per unit of electricity via a PPA or a Contract for Difference (CfD) but storage still sells directly to the market. The third assumes both assets are combined under a hybrid PPA, providing a fixed price for collective electricity production.

Figure 10 shows optimal RES and storage capacities and their NPV when both RES and storage sell electricity directly to the market. The optimal configurations for UK developers are a 90 MW solar farm with 115 MW storage (delivering an NPV of £100 million) and a 200 MW wind farm with 100 MW storage (delivering an NPV of £220 million).

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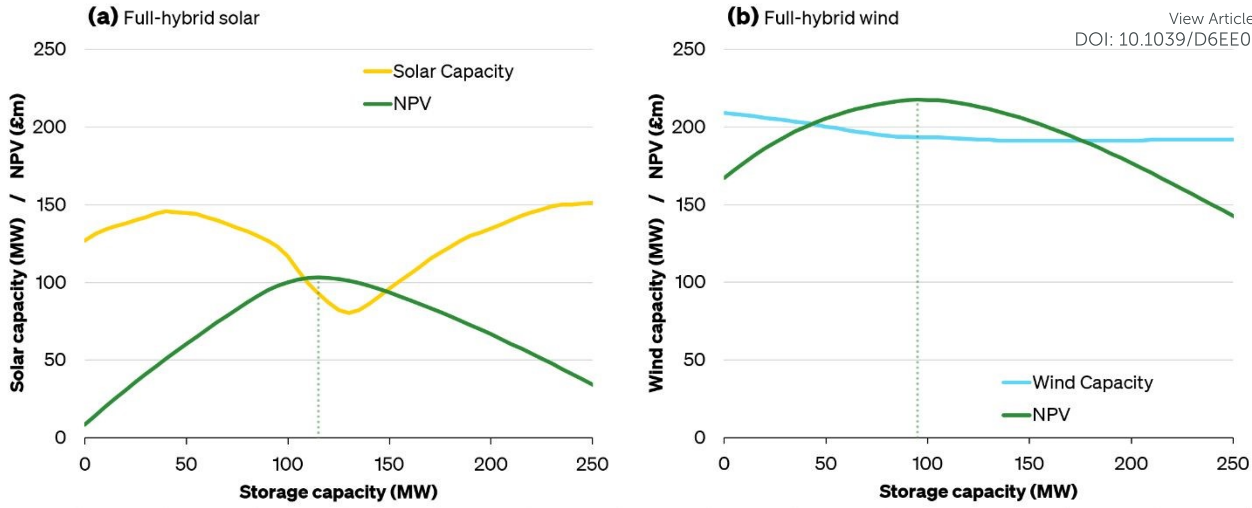

Figure 10: Co-optimised RES and storage capacities and corresponding NPV for different newly built fully hybridised wind and solar projects with a 100 MW grid connection.

Figure 11 shows the optimal renewable and storage capacities when RES receives a fixed price for its output, but storage continues to sell to the open market. For wind and solar, both RES capacities and profits increase as fixed prices increase. As the fixed PPA price rises, the optimal storage capacity stays almost unchanged for solar projects, but declines for wind projects. This difference reflects how each resource shapes arbitrage opportunities. Solar generation is strongly diurnal: output is concentrated in daylight hours and drops to zero overnight. Even at a high fixed price, a larger BESS can still increase NPV by shifting energy into higher-value evening and night-time periods and capturing predictable within-day price spreads. Wind output, by contrast, is more irregular and less tied to a daily cycle, so there are fewer consistent opportunities to charge and discharge in a reliably profitable pattern. As the fixed price increases, it becomes more attractive to invest in additional wind capacity (earning the guaranteed price on more generation) rather than in storage. That shifts the optimum toward a smaller BESS for wind.

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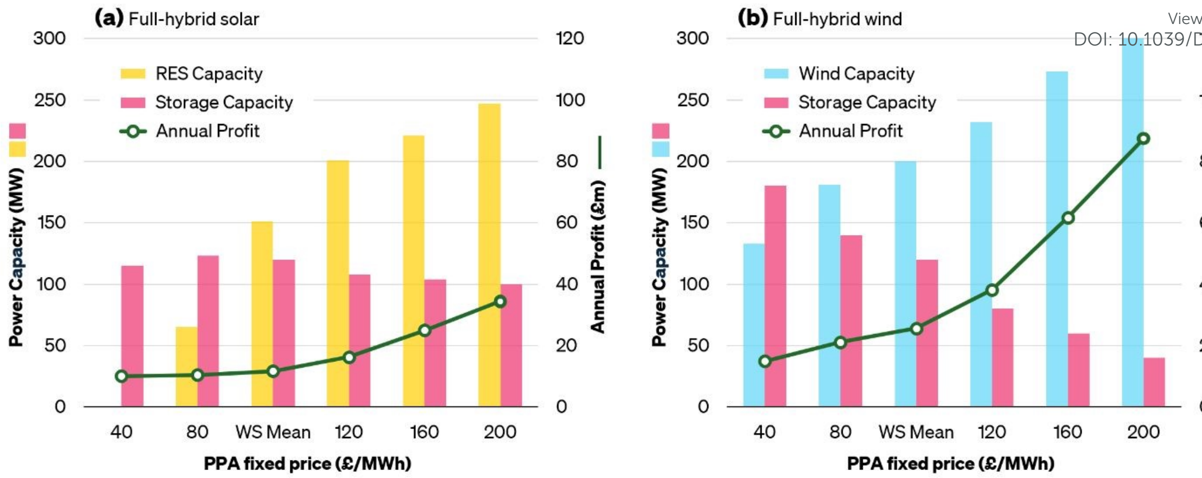

Figure 11: Optimal renewable and storage capacities with corresponding annual profit for various RES fixed prices in full hybrid projects.

Hybrid projects can also operate under a shared PPA, selling a constant (24/7) output of electricity from RES and storage at a fixed price, although this limits storage market participation. Figure 12 illustrates the minimum fixed price required to turn a profit and the required capacities for solar and wind hybrid projects to deliver constant power. Table 5 specifies the capacities and charging dynamics at the minimum fixed price required to turn a profit.

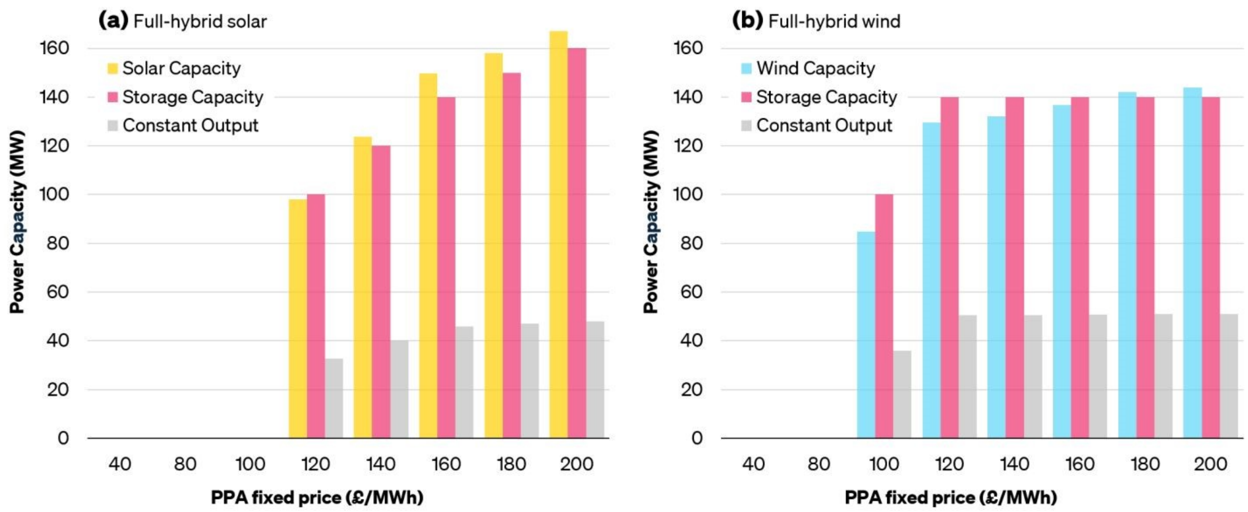

Figure 12: Optimal renewable and storage capacities along with constant power output in the case of 24/7 Hybrid PPAs at different fixed prices.

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Table 5: Summary of findings for full hybrid projects under 24/7 Hybrid PPAs

	Solar Farm	Wind Farm
Minimum PPA Fixed Price	120 £/MWh	100 £/MWh
Storage Power Capacity	100 MW	100 MW
Renewable Power Capacity	98 MW	85 MW
Constant Power Output	33 MW	36 MW
% of PPA output charged from grid	34.9%	18.5%
% of PPA output charged from RES	2.2%	6.5%

4.4 International assessment of full hybrid systems

To expand our analysis to other electricity markets with available price data, some simplifying assumptions were necessary. Market participation is limited to the WS market due to data constraints, and other input parameters were kept constant across countries, except for RES capital costs, which were sourced regionally from the GNESTE database [72].

Figure 13 shows profit-maximising storage capacities and the corresponding IRR for solar and wind farms in each region, assuming full hybrid projects with a fixed RES capacity of 100 MW. The dark blue areas show where stand-alone solar or wind is optimal, with storage increasing profitability in just a few locations. Where solar-storage hybrids improve viability, optimal storage capacities range from 80-120 MW (80-120% of installed solar capacity). Profitability varies widely, with Texas achieving the highest returns and Victoria, Australia showing the lowest. Hybridisation with wind farms show similar trends, with optimal storage capacities in viable locations ranging from 60-140 MW. When only the wholesale market is accessible to the storage system, just 2 of 5 Australian states show an IRR above 8% (i.e. a positive NPV under our assumed cost of capital), due to low prices for RES production and negative-price hours, which are only partially counteracted by revenues from BESS arbitrage. The same is true of solar and solar-storage hybrids in Estonia, Latvia and Lithuania. If wider participation in balancing and capacity markets were included, we would expect positive NPVs across all regions. Most regions favour 4-hour storage, which is used in subsequent modelled scenarios.

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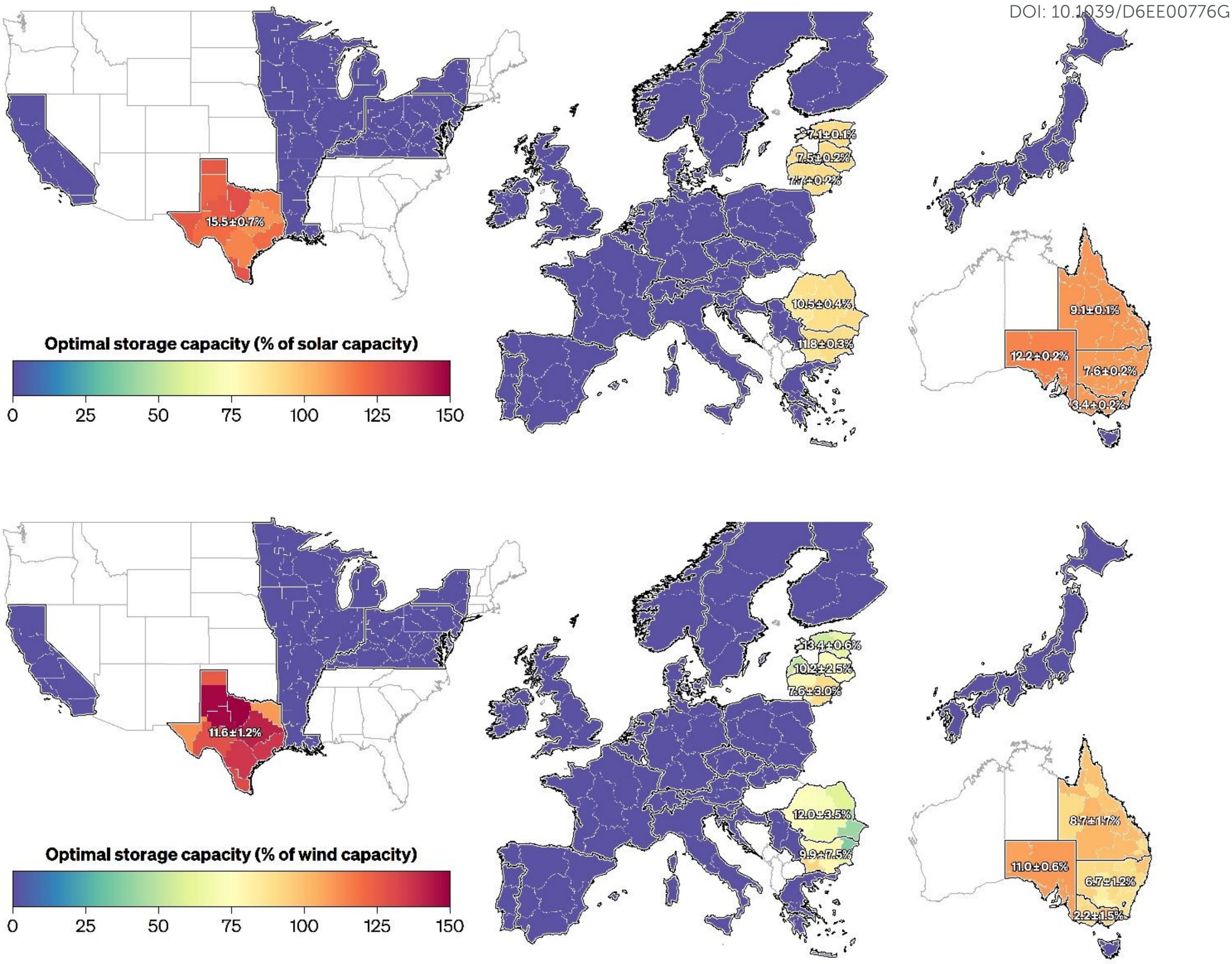

Figure 13: Optimal capacity of the storage system for full hybrid projects providing wholesale arbitrage across the United States, Europe, Japan and Australia: (top) for solar and (bottom) for wind. Inset values give the mean and standard deviation of IRR for regions where hybridisation is optimal.

As with RES developers seeking to hybridise with storage, storage developers may wish to hybridise with RES to increase profitability. Figure 14 shows the optimal solar and wind capacity to add to a 4-hour, 100 MW storage system. Stand-alone storage is optimal across Australia, most of the United States (PJM, MISO, CAISO, NYISO) and Japan, and northern European countries, while hybrid projects are favoured across much of the rest of Europe. The relative capacity factors of solar and wind farms explain regions where hybrids are preferred for one technology but not another. In most areas of Texas (ERCOT), the Chubu region of Japan, and sunny but low-wind areas of Europe (Greece, Switzerland, southern Germany) hybrid solar projects are preferred to stand-alone storage but hybrid wind projects are not. In windy but low-sun regions, such as the Netherlands, Belgium, Denmark, Scotland, the Baltics, and northern Japan, the reverse is true.

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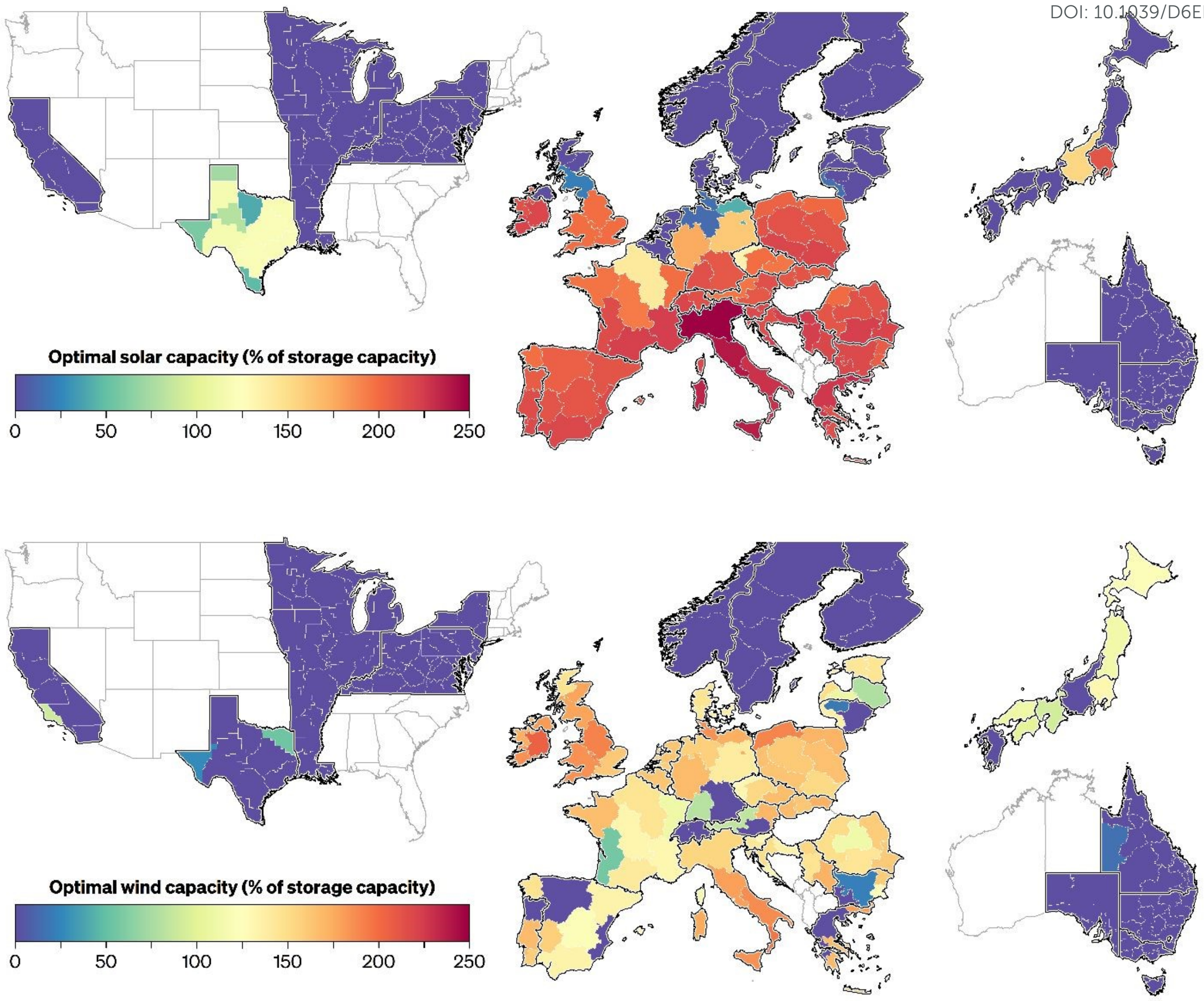

Figure 14: Optimal RES capacity to install in full hybrid projects providing wholesale arbitrage across the United States, Europe, Japan and Australia: (top) solar and (bottom) wind.

Figure 13 suggests that stand-alone renewable assets are often more favourable than hybrids; however, these projects could become financially viable with lower storage costs. Figure 15 shows the maximum storage capital cost per kWh of capacity for a 4-hour storage system to be profitable in a hybrid configuration in each country, using solar as an example, assuming 100 MW fixed capacities for storage, RES, and the grid connection. The maximum cost for viability is unaffected by the renewables capacity factor or production profile, and so only varies by market based on wholesale power prices. As shown previously for stand-alone storage [34], the revenue and thus maximum capital cost of storage correlates well with the logarithm of the standard deviation in wholesale prices (Figure 16). This capital cost threshold for economic viability varies widely. In South Australia, hybrids are viable below £1,560 per kWh as the lack of flexible capacity gives strong price volatility, while in Norway they must fall to £60 per kWh due to competition

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from extensive hydro storage. Across Europe, the threshold costs range from ~£250 per kWh in Italy and Switzerland to £680 per kWh in Romania and the Baltics, with no clear pattern between southern and northern regions. Similarly, in Japan the threshold cost ranges from £250 per kWh in Tokyo to £520 per kWh in Kyushu.

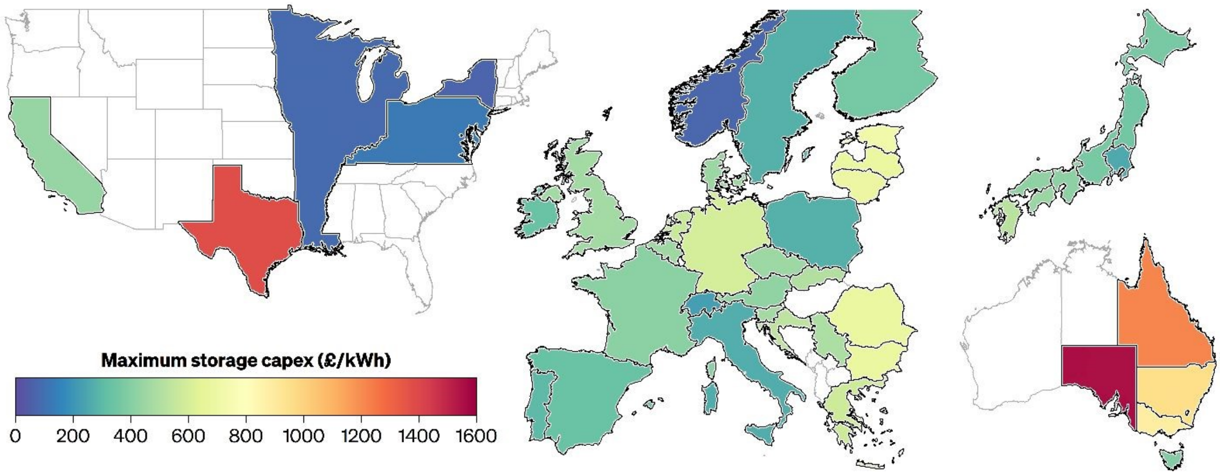

Figure 15: Maximum capital costs of storage systems for solar hybrid projects to turn annual profits from wholesale arbitrage across the United States, Europe, Japan and Australia.

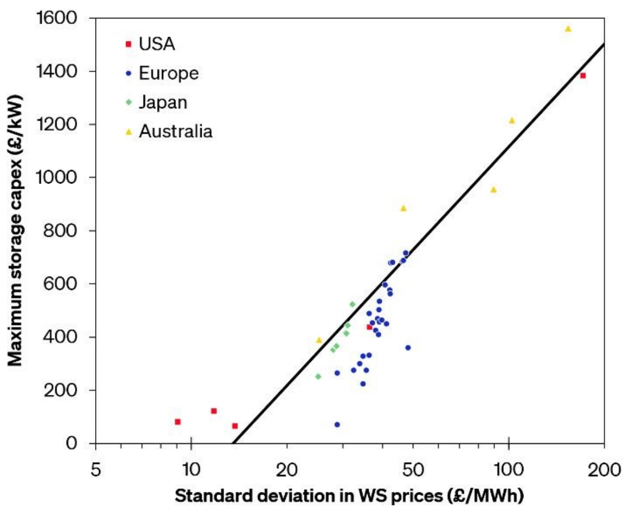

Figure 16: Maximum capital costs of storage systems for solar hybrid projects from wholesale arbitrage, as a function of the standard deviation in each market's hourly wholesale prices. Data points represent the individual power markets within each country or continent.

Full merchant assets which sell to the open market, whether hybrid or stand-alone, generally yield small or negative annual profits; hence, PPAs are essential for ensuring economic viability. Figure 17 shows the minimum fixed price needed under an RES PPA

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to ensure profitability in hybrid wind and solar systems, assuming a 100 MW RES farm, a 4-hour 100 MW storage system, and a 100 MW grid connection, with the storage system operating exclusively in the WS market but able to charge from the grid. Across the US, Europe and Japan, most regions require a fixed price of £60-80 per MWh for solar, or £50-75 per MWh for wind; while in Australia lower prices of £25-45 and £35-55 per MWh are sufficient for solar and wind. As with capital cost, the required PPA scales log-linearly with the standard deviation of wholesale prices, and also with the inverse of capacity factors as less productive regions require the highest PPA. For solar, this includes northern US states such as New York (NYISO) needing £80-90 per MWh and Nordic countries where this must exceed £85 per MWh, reaching over £120 per MWh in Norway. The required PPA for wind in Australia, Japan, Texas and California is comparable to that for solar; however, Southern European countries require higher prices. For example, Italy requires a mean of £30 per MWh for solar but £60 per MWh for wind.

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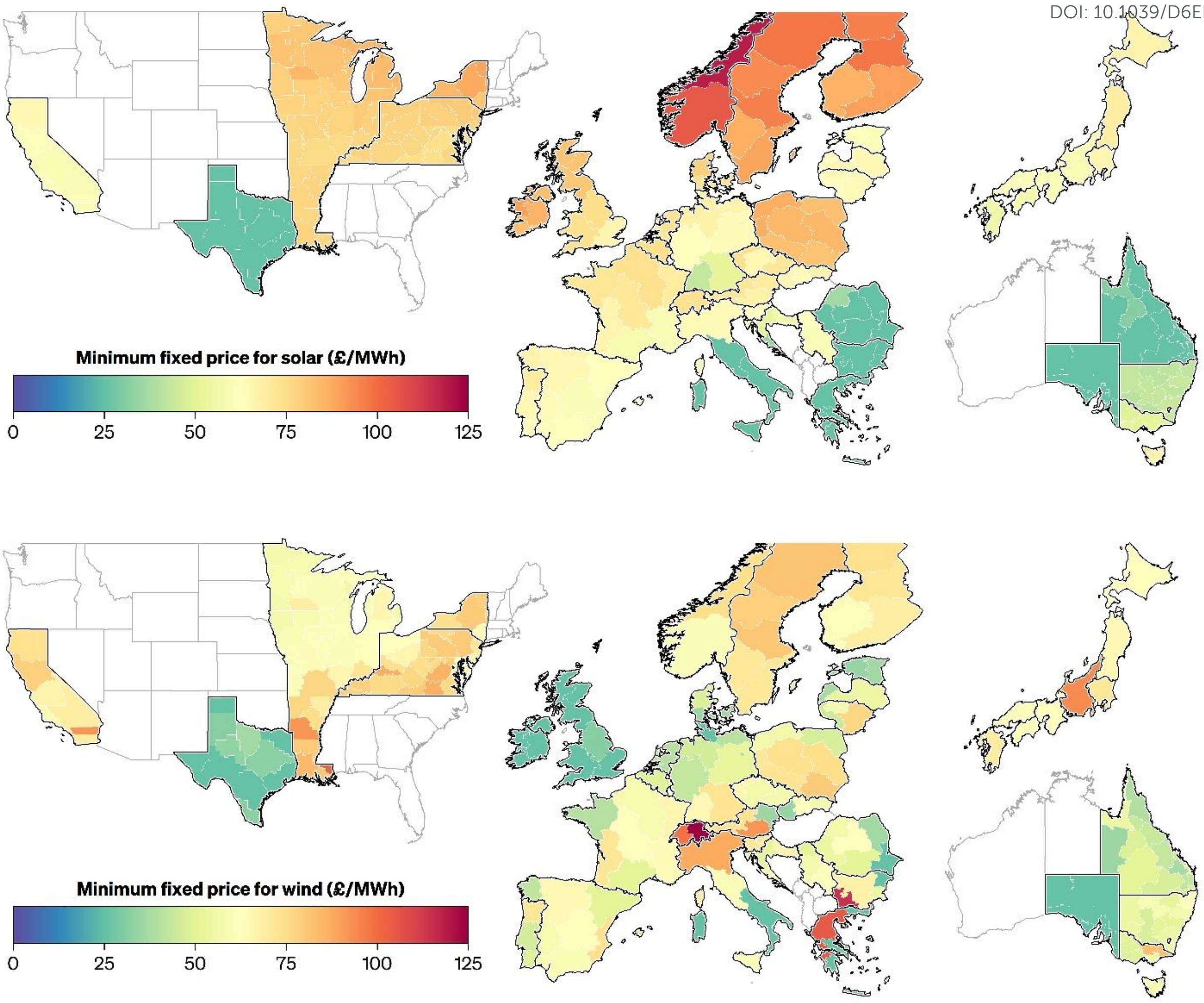

Figure 17: Minimum fixed price for the PPA to ensure positive profit for full hybrid projects providing wholesale arbitrage across the United States, Europe, Japan and Australia: (top) for solar and (bottom) for wind.

RES and storage can be combined in various ways, including solar, wind, or both hybridised with storage. Figure 18 shows the configuration which delivers the highest profits in each region, given a 4-hour, 100 MW storage system and a fixed 100 MW grid connection. Stand-alone storage systems are favoured across almost all Australian regions, the US (except Texas), and Nordic countries. Stand-alone storage is generally favoured where price volatility is high, or where renewable assets typically receive a low price for their output, so utilising the grid connection primarily for wholesale arbitrage realises the greatest profits. In a few regions, solar with storage is optimal (e.g., Texas, Chubu, Greece and Bulgaria), while wind with storage is favoured in other regions (e.g., the UK and Ireland, the Netherlands, Denmark, and the Baltics). Across much of southern and central Europe solar-wind-storage hybrid systems deliver the highest profits, as the

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complimentary output patterns of wind and solar and the ability to store electricity maximise utilisation of the grid connection.

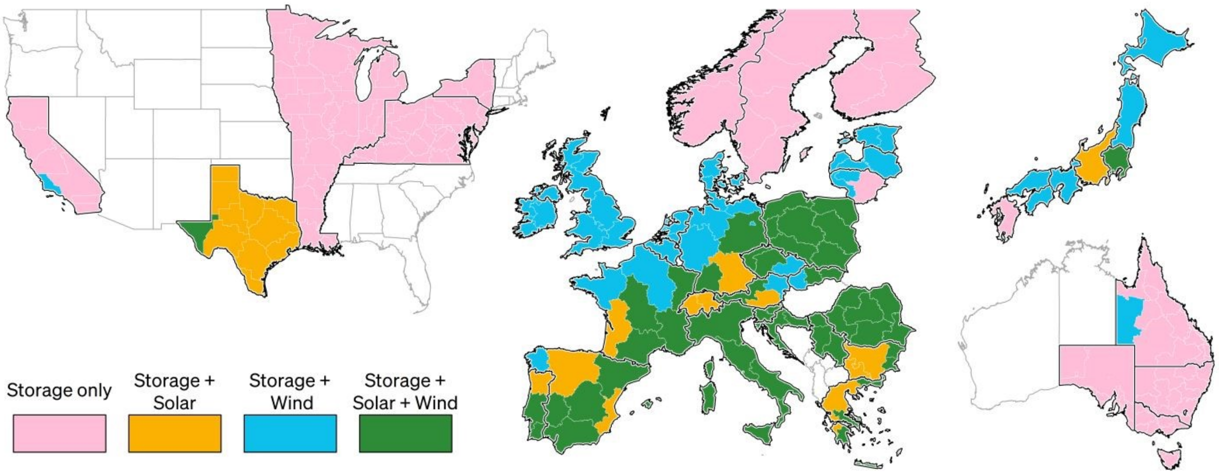

Figure 18: Optimal assets to include in full hybrid projects that provide wholesale arbitrage across the United States, Europe, Japan and Australia.

Figure 19 outlines optimal RES capacities for the regions where hybrid projects are preferred. In nearly all regions, either solar or wind capacity exceeds 100 MW (i.e., the grid connection capacity) and the system therefore benefits from storage reducing curtailment during peak output. Solar hybrid projects show an optimal capacity averaging 215±5 MW, and wind hybrids average 160±15 MW. In solar-wind-storage projects, combined RES capacity follows an ellipse between these points with an average 175±25 MW of combined capacity, and a preference for solar over wind, except in Czechia, Slovakia, and Germany.

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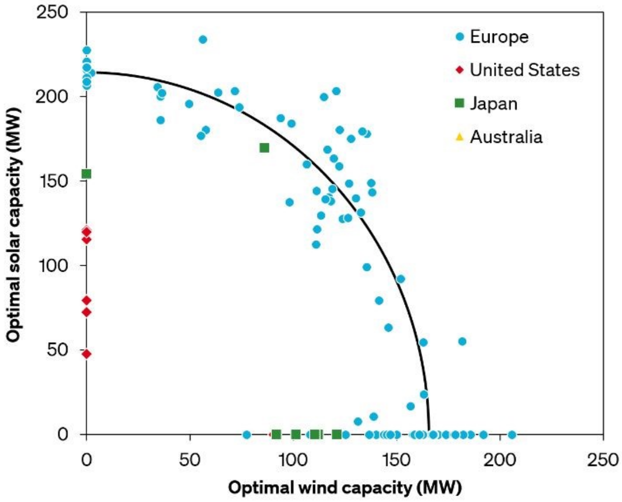

Figure 19: Optimal solar and wind capacities for full hybrid projects with 100 MW of storage and 100 MW grid connection. The thick black line shows the ordinary least squares fit in polar coordinates.

4.5 International assessment of co-located projects

The previous section examined the viability of fully hybrid projects; here, we evaluate co-located configurations where storage and renewable assets are dispatched separately, rather than co-optimised. A central decision for storage developers is whether a stand-alone BESS or a BESS co-located with renewable generation is more profitable. Where co-location is more profitable, we identify the optimal renewable capacity to pair with the storage system.

Figure 20 presents the optimal storage capacity for co-located projects paired with a 100 MW solar or wind farm. In regions where the optimal capacity is greater than zero (Australia, Texas and Eastern Europe), co-located configurations are economically viable, although stand-alone storage may still yield higher profitability.

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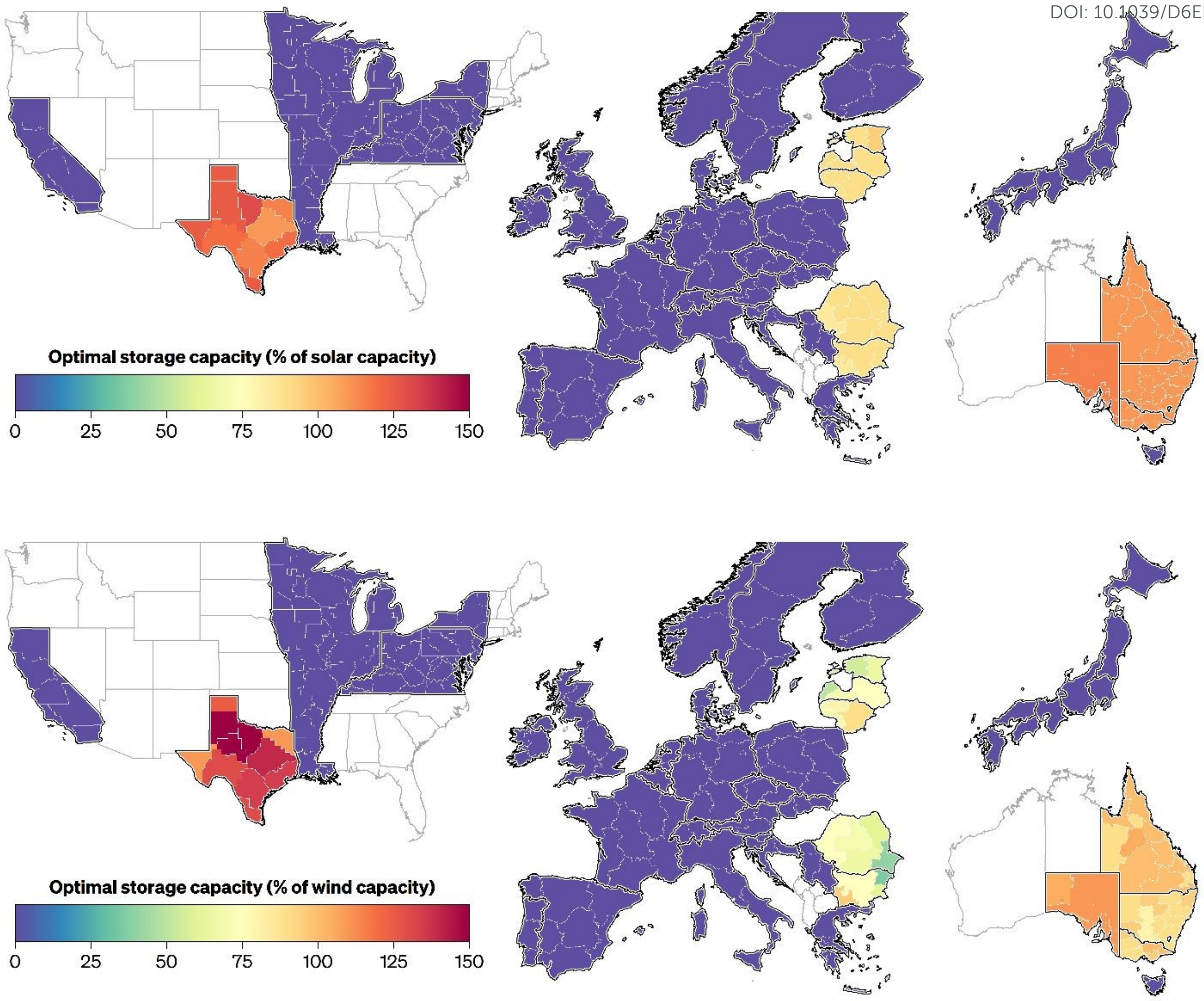

Figure 20: Optimal storage capacity for co-located projects providing wholesale arbitrage across the United States, Europe, Japan and Australia: (top) solar and (bottom) wind farms.

Figure 21 shows the optimal solar or wind capacity to co-locate with a 100 MW, 4-hour storage system in each region. Note that results for the UK differ from the earlier case study because storage is restricted to the WS market here, and the locations being simulated are different. For solar, where co-location is viable, co-located configurations are generally more profitable than stand-alone storage, with the exceptions of Latvia, Lithuania, New South Wales, and South Australia. For wind, co-location is less often viable, and the optimal wind capacities are typically smaller than the corresponding optimal solar capacities.

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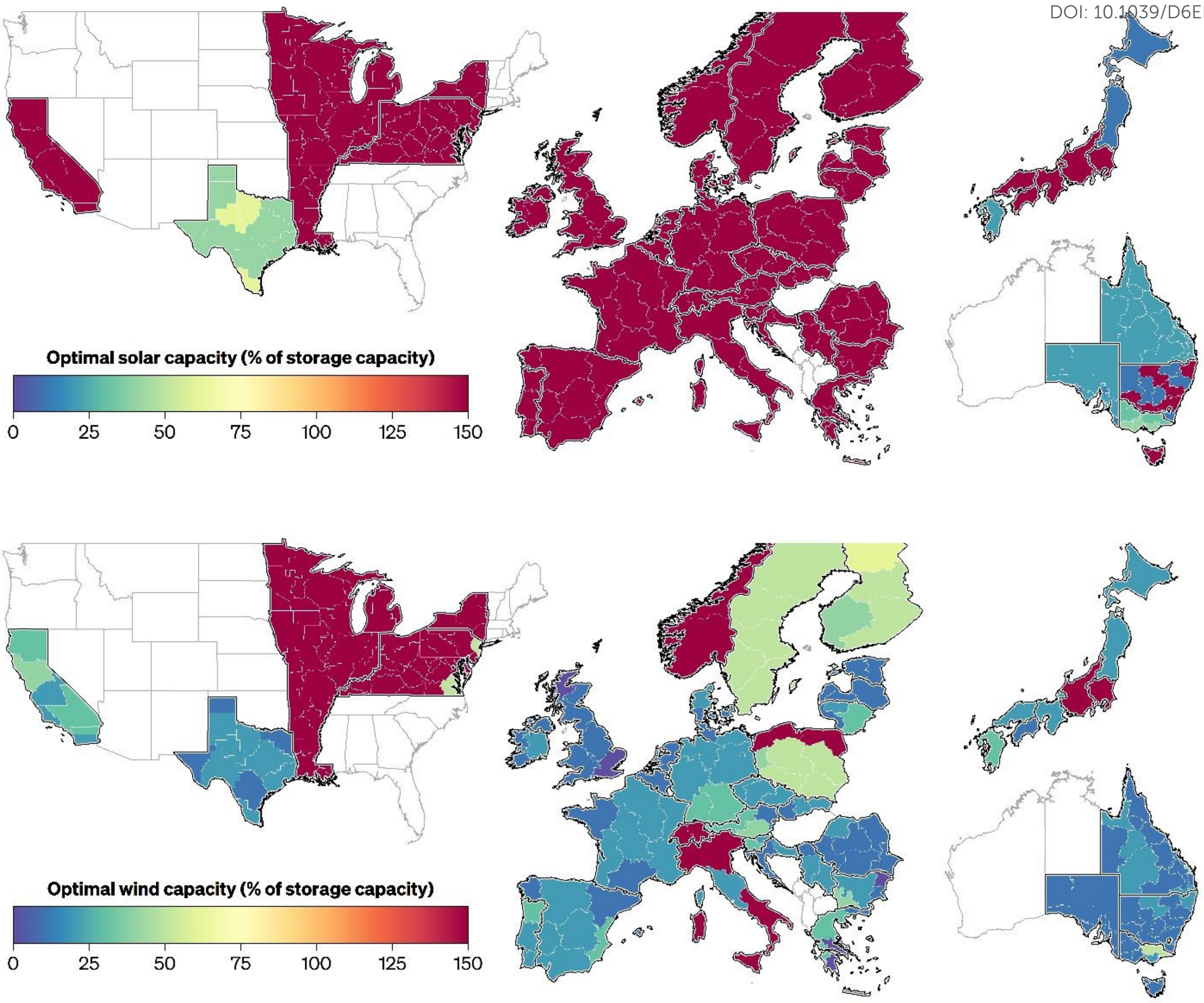

Figure 21: Optimal RES capacity for a storage system to co-locate with when providing wholesale arbitrage across the United States, Europe, Japan and Australia: (top) solar and (bottom) wind farms.

The viability of co-located projects depends strongly on initial grid utilisation from the wind or solar farm. Co-location is economically attractive only when the savings from sharing a grid connection outweigh any revenue losses arising from operational constraints. In regions where initial grid utilisation exceeds 25-30%, co-located configurations are generally less favourable than stand-alone systems.

Solar projects exhibit more uniform initial grid utilisation and typically deploy higher installed capacities, enabling storage to capture value from otherwise curtailed generation. Appendix 14 presents a set of regional case studies that examine these dynamics in more detail and highlight the key drivers of profitability for hybrid and co-located projects.

5 Discussion

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A central challenge for decarbonising power systems is maintaining the momentum of investment in wind and solar power as their deployment matures [73,74]. Although their capital costs have fallen rapidly, the rising share of renewables is eroding their market value due to strongly correlated output and creates constraints around grid access, with long connection queues which threaten to derail future deployment [75,76]. This study explores when, and under what conditions, adding battery energy storage systems (BESS) to utility-scale renewables increases their economic value. It shows that economic viability is highly sensitive to access to multiple revenue streams, the ability charge from the grid alongside the on-site renewables, and to the volatility in power prices.

Our UK case study confirms the view that profitability depends heavily on market access and operating constraints, rather than on resource quality alone. Co-located storage is only likely to be profitable when it can charge from the grid and stack revenues across markets (wholesale, balancing, and ancillary services). If regulators and system operators want storage to act as a stabiliser of renewable revenues (and a substitute for fossil fuels in providing flexibility), the market must allow batteries to provide arbitrage, balancing services, and be remunerated for ancillary services without being trapped in siloed and potentially conflicting participation frameworks. Conversely, where market design restricts stacking or constrains charging from the grid, hybridisation risks becoming economically unviable, as batteries sit behind a congested connection and cannot be fully utilised to increase capture rates. The same logic extends to contract design. Our analysis illustrates why PPAs can determine bankability of hybrid projects. Fixing the price earned by the renewable generator can shift the optimal investment towards greater renewable capacity, and in the case of wind, sometimes to less storage capacity. Contracts that instead pay for a profile of output (either constant or shaped hybrid PPA contracts) can require substantial capacity and rely heavily on grid-charging to meet firmness targets. This has direct relevance to the credibility and carbon accounting of "24/7" round-the-clock clean energy procurement.

Storage tends to be underutilised if the co-located renewable asset has export priority or if storage is limited to a single revenue stream. The general intuition that hybridisation stabilises renewable revenues is true, but we find it is conditional. Fully hybridised projects outperform simple co-location because coordinating the dispatch of both assets allows the portfolio to be optimised against scarcity of connection capacity, raising capture rates and grid-connection utilisation. However, from the viewpoint of a merchant storage developer,

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a stand-alone battery with its own connection can still deliver higher returns when a grid connection is available.

Grid access has become a central non-monetary barrier in several markets, for example the UK [77] and US [78]. Although we find that a stand-alone BESS with an unconstrained connection can outperform a co-located system with constrained dispatch, co-location can still bring value where using an existing grid connection avoids lengthy connection queues and network costs. Project appraisers should evaluate the connection-adjusted NPV of projects, balancing the opportunity cost of restricted dispatch against the reduced time to connect, queue attrition risk, and cost of connection.

Our international analysis shows wide geographic variation, and there is no single best configuration for renewable-storage hybrids. Countries differ strongly in their electricity price volatility and renewable productivity. Stand-alone storage is typically optimal in Australian and many US markets, while hybrid systems tend to be comparatively stronger across much of Europe and in Texas. Clear structural patterns are also seen, with fully merchant storage usually marginal or loss-making when restricted to wholesale markets, implying that revenue stacking or long-term contracting (e.g. through PPAs) would be required for viability. These results reinforce the view that developers cannot readily transfer business models or sizing strategies between markets [34], therefore policy should not promote hybrids uniformly across regions, but instead target markets where negative pricing, curtailment, and multi-market access coexist. For example, Turkey mandated in 2022 that new wind and solar farms must install battery storage equal to their rated capacity [79]. While this has led to Europe's largest pipeline of energy storage projects [79], the use of a nationwide fixed ratio will lead to under- and over-sized batteries depending on the output profile of the renewable asset they co-locate with. More broadly, mandating co-located storage increases the capital cost of renewables projects which could in turn deter developers.

The international co-location results reinforce the UK finding that shared connections create value only under specific conditions. A useful practical indicator is initial utilisation of the grid connection (i.e., the capacity factor of the renewable asset). Where baseline utilisation is high (above ~30% in this study), co-location tends to be unfavourable because the BESS has limited remaining headroom to operate. Co-located solar is generally more viable than wind because the diurnal pattern of solar power creates predictable windows (overnight) when the grid connection is available, and clear arbitrage opportunities on mosy days. In contrast, the slower variability in wind output can keep the connection congested for several days at a time, reducing storage utilisation.

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Across the markets explored here, longer-duration batteries with 4-hour discharge capability tend to be the most cost-effective compromise between capital cost, arbitrage opportunity, and degradation-limited throughput. Shorter (e.g. 1-hour) duration batteries struggle to monetise enough energy shifting and very long durations narrow the band of profitable power capacities. This mirrors the shift seen within the industry from short-duration frequency response towards longer-duration systems providing daily energy shifting [75,80].

Limitations of our work temper how far these conclusions should be generalised. The international results should be interpreted as conservative for regions where balancing, ancillary service, or capacity revenues are material. For example, in Australia only a subset of regions achieve positive NPV under wholesale-only participation, and broader market access would improve profitability. Greater availability of open data on ancillary market prices would enable future international multi-market studies, which could utilise the framework developed here. The revenue-stacking optimisation relies on historical production and price data, and in the UK case, a particular set of balancing and ancillary market conditions. Repeating representative years of dispatch across project lifetimes neglects the variation that should be expected with structural changes in future power prices (e.g. as ancillary service saturation evolves). Both financial parameters (discount rates and technology costs) and technical parameters (battery degradation and conversion efficiencies) are represented with tractable approximations, but these are highly project-specific, and in the case of technical parameters, dependent on operating and environmental conditions. Finally, the optimisation takes market prices and available volumes as exogenous, and not influenced by individual storage projects. This is reasonable, given that in the markets considered, no single storage project can be a price maker. However, at scale, storage and hybrids can compress spreads and reshape balancing needs, so the private optimum may diverge from the system optimum once equilibrium feedbacks are included.

These caveats motivate several research priorities. Future work should test the robustness of our conclusions across multiple historical years and prospective scenarios, explicitly incorporating evolving renewable build-out, curtailment driven by network congestion, and endogenous price effects as storage deployment grows. A next generation of hybrid valuation models could combine co-optimisation across a richer set of services (including capacity and locational network signals where applicable), more physics-informed degradation models tied to duty cycles and warranty structures, and probabilistic representations of bid acceptance and service activation [81]. Specific case

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studies could consider detailed project finance and performance data to more accurately assess profitability and optimal configurations. This analysis suggests that regulatory frictions can outweigh large differences in resource quality; hence, comparative work is needed on how interconnection rules, network charges, and "hybrid definitions" in regulation affect revenue stacking. Finally, linking private profitability to public value requires integrating emissions-aware dispatch and carbon accounting into "firm" procurement products, so that the appetite for shaped and 24/7 contracts strengthens [82], rather than undermines, decarbonisation.

6 Conclusions

This study shows that the economic case for renewable-storage hybrids depends on the technologies, system configurations, and rules that govern how storage can use scarce grid connection capacity and monetise flexibility. Our framework for optimising the revenue-stacking dispatch provides a transferable method for identifying the conditions under which co-located and fully-hybrid renewable-storage configurations create economic value, and where stand-alone storage is preferable. Unlocking the value of renewables and batteries will depend critically on market access and regulatory designs that preserve the optionality that makes storage valuable in the first place.

As storage costs continue to fall and the share of variable renewables increases, hybridisation will become increasingly attractive, with growing interest in "24/7 renewables" where solar, wind and batteries provide firm round-the-clock electricity [83]. Identifying the optimal regions and technology configurations for such systems will support this next step in power sector decarbonisation.

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7.1 Funding declaration

This research received no external funding.

7.2 Author contributions

ML contributed to conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing the original draft, visualization, and project administration. OS contributed to conceptualization, methodology, validation, resources, writing – review and editing, supervision, and project administration. NJ contributed to methodology, validation, writing – review and editing, and project administration. IS contributed to conceptualization, methodology, validation, resources, writing – review and editing, supervision, and project administration.

7.3 Conflicts of interest

There are no conflicts to declare.

7.4 Data availability statement

The data supporting this article have been included as part of the Supplementary Information. Supplementary information: Appendices 1 to 14. This study was carried out using publicly available data from the Renewables.ninja model at https://www.renewables.ninja.

Nomenclature

Symbol	Description	Symbol	Description
AC	Alternative current	**ITC**	Investment Tax Credit
AI	Artificial Intelligence	**LCOE**	Levelised Cost of Electricity
BM	Balancing mechanisms	**NPV**	Net Present Value
BOS	Balance-of-System	**OPEX**	Operational expenditures
CAPEX	Capital expenditures	**PBP**	Payback Period
DC	Dynamic containment	**PPA**	Power Purchase Agreement
DC*	Direct current	**PTC**	Production Tax Credit

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DCH	Dynamic containment High	**RES**	Renewable Energy Sources
DCL	Dynamic containment Low	**SA**	Stand-alone
GC	Grid-connected	**T&D**	Transmission & Distribution
HRES	Hybrid Renewable Energy Systems	**UK**	United Kingdom
IEA	International Energy Agency	**WS**	Wholesale
IRR	Internal Rate of Return		

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Data availability statement

The data supporting this article have been included as part of the Supplementary Information. Supplementary information: Appendices 1 to 14. This study was carried out using publicly available data from the Renewables.ninja model at https://www.renewables.ninja.