Supplementary Information (SI) for Energy & Environmental Science.

Supplementary Material

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Appendix 1: Hybrid systems coupling technologies

Table 1: Advantages and drawbacks of coupling technologies for hybrid systems

	Advantages	Drawbacks
AC coupled	- Good reliability - Ready for grid connection - Easy multi-voltage and multi-terminal matching	- Need for synchronised frequency over every component - Need for power factor and harmonic distortion correction
DC coupled	- No synchronisation needed - Single wired connections	- Collapse of the whole system if bus or DC/AC inverter fail - Concerns about voltage compatibility
DC/AC coupled	- Higher overall efficiency - Lower system cost	- Increased complexity in control and management of the system

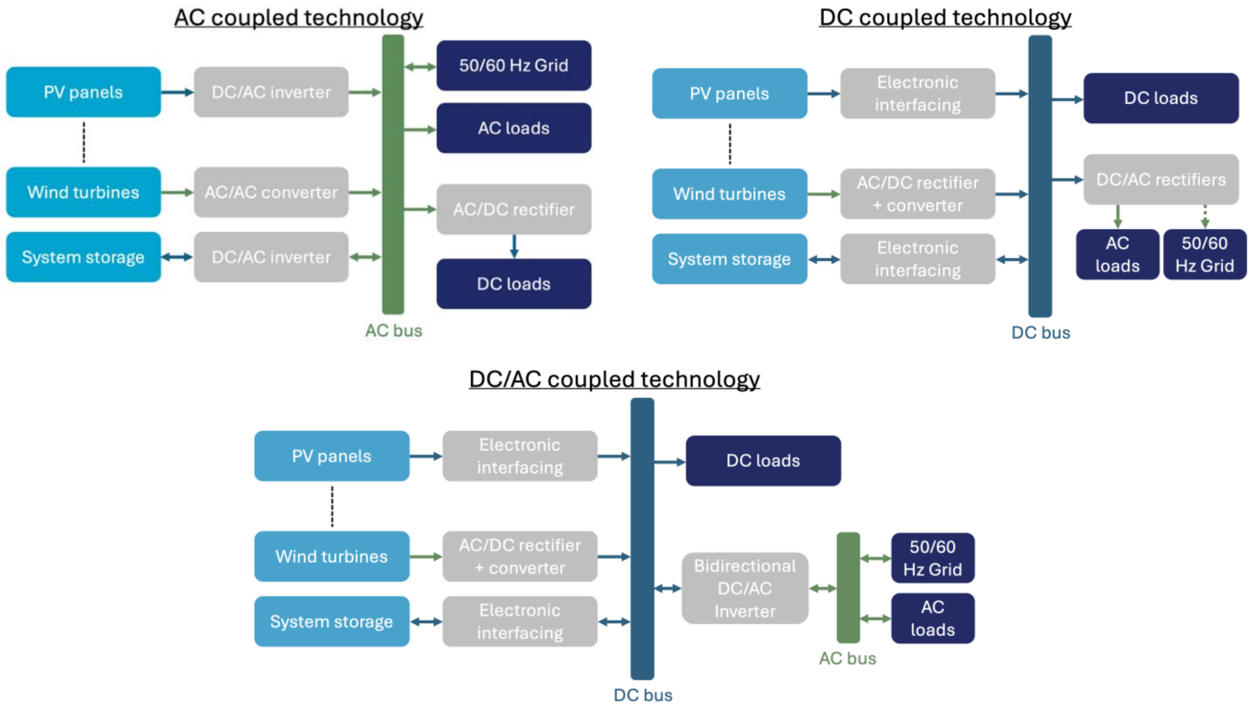


Figure 1: Description of the different coupling types

Appendix 2: Policy and support for hybrid systems

Co-located projects require supportive policies and streamlined regulations to ensure feasibility. As of 2021, few studies addressed hybrid project regulations, with gaps in policy often hindering deployment due to varying rules for different assets [1,2].

In the US, credits like the PTC and ITC target stand-alone solar or wind but overlook hybrids, while Germany's RES Act (EEG) focuses on renewable generation without addressing hybrid setups [1]. Spain's regulations allow storage integration into existing projects without new grid permits, though storage capacity is limited [3].

In the UK, Ofgem's 2023 guidance grants hybrids access to support schemes like the Renewable Obligation, with further plans to allow storage co-location under Contracts for Difference [4]. Germany's 'Innovation Tenders' offer premiums for renewables-plus-storage projects, valuing their grid services [5]. Amid evolving policies, investors are increasingly exploring new types of Power Purchase Agreements (PPAs) to secure revenues for hybrid projects.

Co-located projects combining RES with storage can offer flexibility through three types of Hybrid PPAs [6]:

- **Renewable PPA with a Storage Capacity Agreement:** Involves a traditional PPA for the renewable asset and a capacity agreement for the storage system, which must be available during specified periods. Utilities may provide fixed payments for this availability, enhancing grid reliability.
- **Shaped Renewable PPA:** Combines renewable and storage assets in one agreement, allowing buyers to specify an hourly demand profile that the seller meets. Asset owners might also purchase positions on the open market.
- **Blended Renewable & Storage Premium PPA:** Integrates generation and storage, applying a premium to each electricity unit transferred, allowing for profile shaping and operational adjustments.

PPA type depends on asset location, operational specifics, and seller risk tolerance. Hybrid PPAs can combine revenues from ancillary services with traditional PPAs but require careful management [6].

Appendix 3: Optimisation methods

Table 2: Definition of key traditional methods with strengths and weaknesses [7–11]

Probabilistic Method	
Focuses on evaluating one or two system performance indicators while accommodating multi-objective functions and non-linear responses. Utilises long sequences of weather data, calculating probability density functions for power generation to account for variations in solar irradiance and wind speed [8].	
+	**–**
Easy to implement Time-series data not needed	Not suitable for optimal solution finding Can't present a dynamic effort
Graphical Construction Method	
Addresses optimisation problems with two variables by visually representing their interactions. Involves plotting constraint functions on the same chart and comparing the feasible region with the objective function contours [9].	
+	**–**
Easy to understand Low Complexity	Lack of flexibility Can't deal with high dimensional problems or too many variables
Iterative Method	
The evaluation criteria evolve until an optimal configuration is identified, yielding an approximate solution. Simulations continue on a computer until a termination criterion is met. Common iterative methods used include Hill Climbing, Dynamic Programming, Linear Programming, and Multi-objective Programming [10].	
+	**–**
Easy to implement Time-series data not needed	Unable to optimise specific attributes High computing effort
Analytical Method	
Uses mathematical formulations and theoretical analysis to determine system characteristics and parameters, with a focus on economic viability. Typically relies on historical data to provide insights into trade-offs and constraints in decision-making processes [7].	
+	**–**
Fast and easy to calculate Provides a unique solution	Requires long-term meteorological data Limited degree of flexibility Only two parameters can be optimised

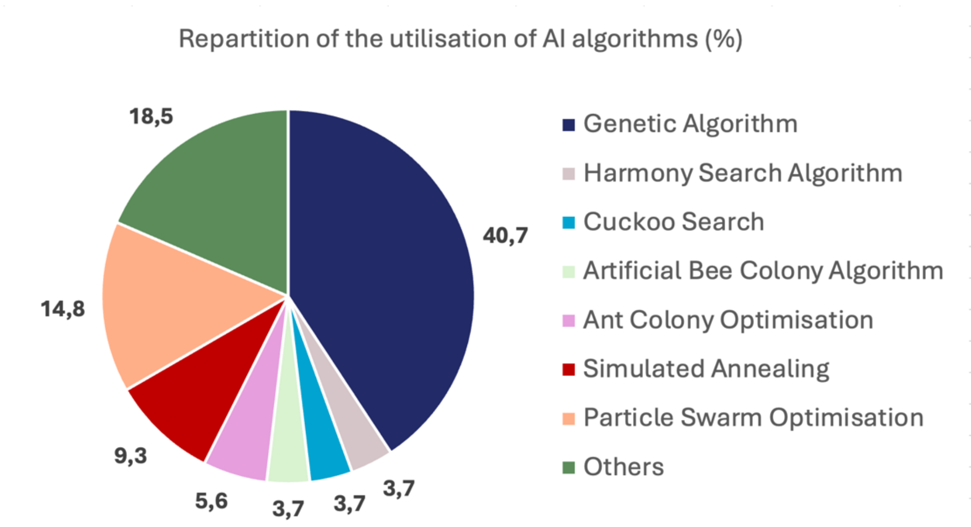


Figure 2: Proportion of key AI algorithms in the sizing of HRES. Source: [12]

Table 3: Inputs and Outputs of the main software tools for the design of HRES. Source: [10]

	HOMER	iHOGA	Hybrid2	RETScreen	TRNSYS
Inputs					
Load demand	✓		✓		
Resources data	✓	✓	✓	✓	✓
Component data	✓	✓	✓		
Constraints	✓	✓			
Controlling a system	✓			✓	
Data on emissions	✓	✓		✓	
Data on the economy	✓	✓			
Financial information	✓		✓		
Models taken from own collection	✓				✓
Outputs					
Size optimisation	✓	✓	✓	✓	
Technical evaluation	✓	✓	✓	✓	✓
Financial assessment	✓	✓	✓	✓	
Environmental analysis	✓			✓	
Multi-objective optimisation	✓	✓			
Life-cycle emissions	✓	✓		✓	
Analytical probability	✓	✓		✓	
Risk assessment and sensitivity analysis	✓			✓	✓

Appendix 4: Evaluation criteria

Table 4: Evaluation criteria used in the literature for the optimisation of HRES. Source: [7,8,11]

Evaluation criteria	Description	Equation
Reliability		
Loss of Load Expected (LOLE)	Average number of hours when the load is expected to be higher than the generation capacity	$LOLE = \sum_{h=1}^{H} \sum_{i \in S} P_i \times T_i$
Loss of Load Probability (LOLP)	Ratio of the total energy deficit to the load demand over a specific period	$LOLP = \frac{\sum_{h=1}^{H} ES(h)}{\sum_{h=1}^{H} LD(h)}$
Loss of Energy Expected (LOEE)	Expected value of energy that has not been provided	$LOEE = \sum_{h=1}^{H} \sum_{i \in S} P_i \times LOE_i$
Loss of Power Supply Probability (LPSP)	Probability that an unability to meet load demand results in a power shortage	$LPSP = \frac{LOEE}{\sum_{h=1}^{H} LD(h)}$
Economic		
Levelized Cost of Energy (LCOE)	Unit cost of energy	$LCOE = \frac{Discounted\ total\ cost}{Discounted\ total\ energy\ produced}$
Life Cycle Cost (LCC)	Net Present Value sum of all costs	$LCC = C + OM_{npv} + R_{npv} - S_{npv}$
Annualized cost of the system (ACS)	Annual cost of the system including capital cost, O&M cost, fuel cost, and replacement cost	$ACS = C_{a,cap} + C_{a,O\&M} + C_{a,fuel} + C_{a,rep}$
Net Present Cost (NPC)	Difference between the present value of cash outflows and cash inflows	$NPC = ACS \times CRF$
Environmental		
Carbon Footprint of Energy (CFOE)	Total amount of emissions per unit of energy generated during the system lifetime	

CRF corresponds to the Capital Recovery Factor and is linked to the discount rate by the following equation:

$$CRF = \frac{r(1+r)^n}{(1+r)^n - 1} \quad (1)$$

Where r represents the discount rate and n the project lifetime.

Table 5: Review of methods used and characteristics of renewables-plus-storage found in the literature.

Sizing method	Energy sources	SA / GC	Indicators	Objective functions	Reference
Traditional methods					
Graphical	PV/WT/Battery	SA	Economic	Minimise cost	13
	PV/WT/Hydrogen	SA/GC	Economic Environmental	Minimise cost and emissions	14
Iterative	PV/WT/Battery	SA	Economic	Minimise LCOE	15
	PV/WT/Battery	SA	Reliability	Minimise LPSP	16
	PV/Biomass/Battery	SA	Economic	Minimise total cost	17
Probabilistic	PV/WT/Battery	SA	Reliability	Maximise reliability	18
	WT/Battery	SA	Reliability	Maximise reliability	19
	PV/WT/Battery	SA/GC	Reliability	Minimise LPSP	20
	PV/WT	SA/GC	Economic	Minimise cost	21
	PV/Battery/DG/ Hydrogen	GC	Economic	Maximise NPV	22
Analytical	PV/WT/Battery	SA	Technical Economic	Minimise LCOE	23
	PV	SA	Reliability Technical	Minimise LOLP, Capacity of PV	24
	PV/WT	GC	Economic	Minimise LCOE	25
	PV/WT/Battery	SA	Economic	Minimise cost	26
	PV	SA	Economic	Minimise PBP	27
	PV/Battery/ Seasonal storage	SA/GC	Economic Environmental	Minimise cost and emissions	28
	PV/Battery/ Seasonal storage	SA/GC	Economic Environmental	Minimise cost and emissions	29

Appendix 5: Methodology Details

Data collection

This section outlines the strategy employed for gathering the various types of information required for the optimisation model computations.

Data collection was necessary for the parameters input in the model, which include the characteristics of the renewable assets, storage system, hybrid system coupling, as well as project details and financial/cost parameters. These data were gathered from various sources, including academic papers, company websites, and interviews. Specifically, storage system costs and efficiencies were obtained through a benchmarking process based on data provided by interviewees. This approach allowed for a comparison between literature-based data and real-world modelling insights.

The electricity production data for the renewable assets was retrieved using the API provided by the Renewables.ninja platform [30,31]. This API enables the download of hourly power outputs for wind or solar farms, based on the input parameters specified in Table 6 as an example. These parameters correspond to the Lyneham Solar Farm site, reflecting the characteristics used in this study.

Table 6: Solar production characteristics entered in Renewables.ninja

Parameter	Value
Latitude, Longitude of the location	51.509, -2.0
Installed renewable capacity	1 MW
Period of time considered	01/01/2023 – 31/12/2023
System parameters	
- System loss	0
- Tilt angle	35
- Azimuth angle	180

For modelling purposes, the capacity is fixed at 1 MW and later scaled by the actual renewable capacity in the model. The system loss is set to 0, as losses are already accounted for within the model.

Electricity price data for the various markets considered in this study was collated over the period from 2019 to 2023 from various market operators, as detailed in [32]. Additionally, data on the volumes required by the system operator for BM and DC markets was gathered through the publicly available sources of ESO [33] and ModoEnergy API [34].

Data cleaning

The goal of the data cleaning algorithm was to standardise the data and generate half-hourly inputs suitable for processing by the optimisation model. The different phases of the cleaning process are described as follows:

- **Fill in Missing Values:** Missing values were addressed through linear interpolation, using preceding and succeeding values to estimate and complete the gaps.
- **Date and Time Treatment:** The electricity price data contained dates in various formats. All files were standardised to the format '%Y-%m-%d %H:%M:%S'.
- **Local Time vs. Global Time:** While electricity price files where using local time for their data, renewable production was put under UTC time zone. To adjust the data to local time, values at the beginning and the end of the year were inverted to have a file going from 01-01 00:00 to 12-31 23:00.
- **Time interval Resampling:** Both electricity price and renewable production data were resampled to 30-min time intervals using linear interpolation if necessary.
- **Power Unit Conversion:** Renewable energy production was collected as kilowatts. Data was converted to Megawatts to ensure consistent unit with the rest of the programming.
- **Time Period Filtering:** Data was then filtered between the start date and the end date wanted and inputed for the simulation.

This algorithm is subsequently called by the optimisation model during the simulation and returns a Pandas DataFrame, which is then used as an input for the optimisation process.

Half-hourly data computation

This section presents an example of WS prices and renewable production data for the Lyneham Solar Farm case study and the year 2023.

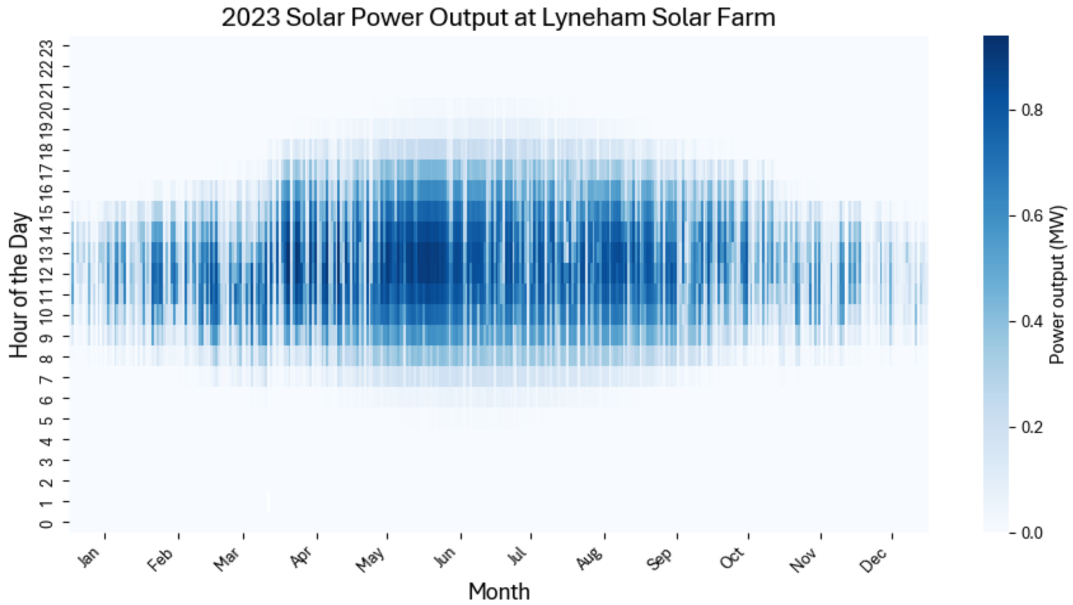


Figure 3: Solar power output of a 1 MW solar farm at the site selected for the year 2023

Figure 3 illustrates the hourly solar power output for the Lyneham Solar Farm throughout the entire year of 2023. Similarly, Figure 4 depicts the UK day-ahead electricity prices for each hour of the day throughout the entire year.

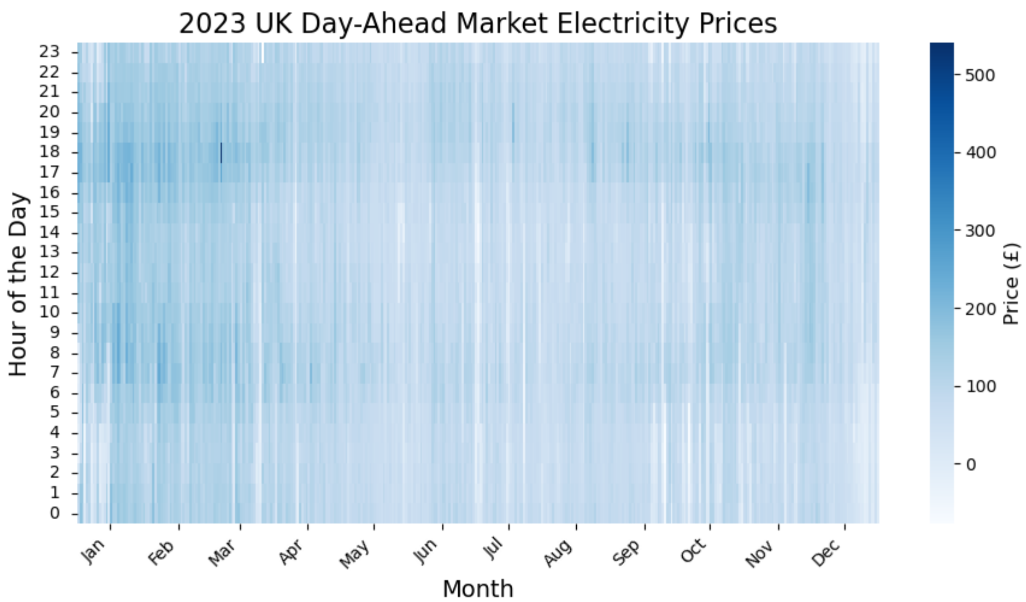


Figure 4: Electricity prices in the market of the site selected throughout the year 2023

Finally, Figure 5 illustrates the frequency of electricity prices across different intervals. It shows that the most common interval is £80-100/MWh, while the majority of prices fall within the range of £60-120/MWh. In addition to these prices, negative prices were observed for 43 hours in 2023.

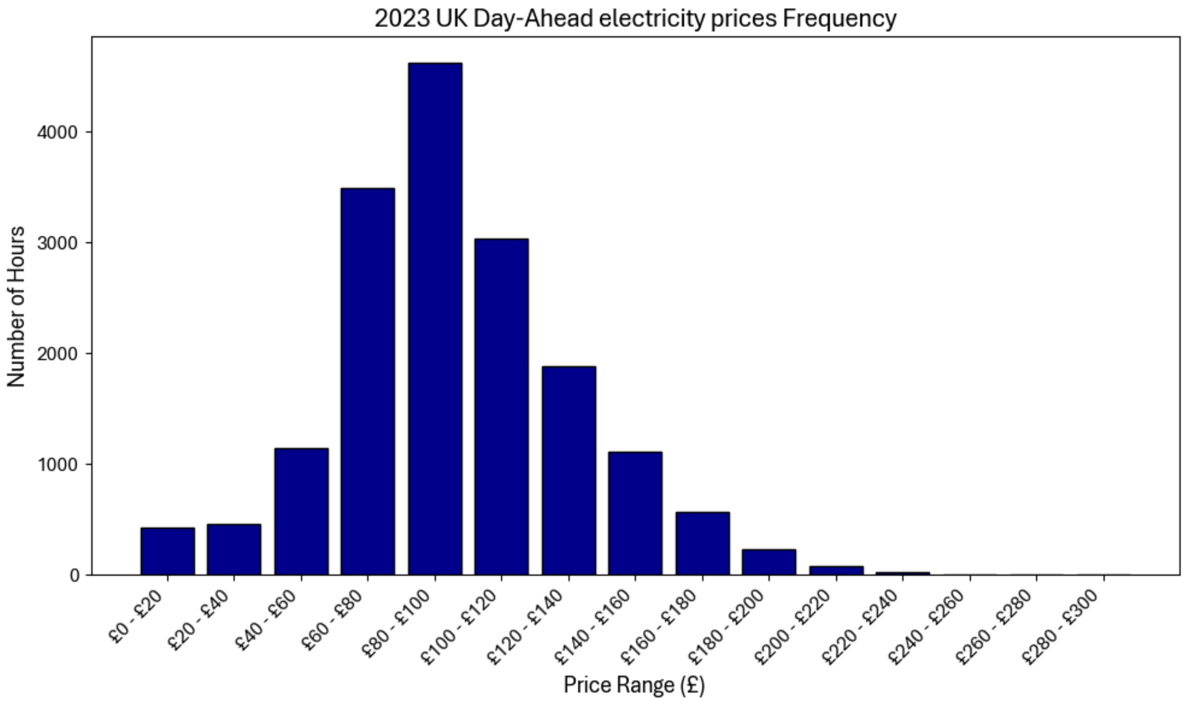


Figure 5: Frequency of UK WS electricity prices in 2023

Parameters data description

Table 7: Details of parameters alongside the values used and their sources

Description	Value	Unit	Source
Storage charging efficiency	0.93		[32]
Storage discharging efficiency	0.93		[32]
DC-DC connection efficiency	0.99		[35]
DC-AC connection efficiency	0.95		[35]
AC-AC connection efficiency	0.98		[35]
AC-DC connection efficiency	0.95		[35]
Proportion of DCL reserve activated	0.1		Interviews
Proportion of DCH reserve activated	0.1		Interviews
Variable O&M cost of the storage system	0	£/MWh	[36]
Variable O&M cost of the solar production	0	£/MWh	[36]
Variable O&M cost of the wind production	0	£/MWh	[36]
Storage depth-of-discharge	0.8		[32]
Storage self-discharge	0.0002	Per day	[37]
Storage calendar lifetime	13	years	[37]
Storage cycle lifetime	4,500	cycles	[37]
Allowed cycles per day	2		[38]
Solar fixed operational cost	15,400	£/MW/yr	[39]
Wind fixed operational cost	25,400	£/MW/yr	[39]
Grid connection cost	67,250	£/MW	Interviews
Time sensitivity of the data	0.5	hours	–
Number of time steps	17,520		–
Project duration	20	years	[40]
Discount rate of the project	0.08		[40]

Operational and capital costs for the storage system were initially gathered through interviews and subsequently cross-referenced with publicly available data to ensure accuracy. These costs, expressed in 2023 £, represent overnight costs for the system. They are provided below:

Table 8: Storage system capital and operational costs

Costs	1 hr	2 hrs	4 hrs
Storage system CAPEX (£/MW)	249,185	387,408	605,134
Storage system OPEX (£/MW/yr)	4,720	6,740	10,785

Using the GNESTE database [39], the study gathered and applied continent-specific capital costs for solar and wind farms summarised below:

Table 9: Solar and wind capital costs considered per continent

Costs	Europe	North America	Oceania
Solar farm CAPEX (£/MW)	746,440	918,450	785,890
Wind farm CAPEX (£/MW)	1,342,960	1,240,390	1,339,000

Scenario variables

The scenario variables outlined below enable the modelling of various project configurations. They allow for adjustments to the type of renewable assets and their revenue models, the coupling and coordination of the assets, and the operational strategies of the storage system. Additionally, these variables provide the option to either optimise the renewable capacity or keep it fixed.

Table 10: List of variables for scenario configuration

Symbol	Description
$Generation_{type}$	List indicating the type of RES assets involved: *['solar']* or *['wind']* or *['solar', 'wind']*
$Coupling_{type}$	List of booleans specifying the type of coupling between the assets: *['AC coupling', 'DC coupling', 'DC-AC coupling']*
$Fixed\_price_{RES}$	The asset operates as a full merchant if the variable is set to 0, or under a fixed price contract if set to another value
$Bool_{opti\_RES}$	Indicates whether the RES capacity is optimised (*True*) or fixed (*False*)
$Bool_{coord\_assets}$	Specifies if the assets coordinate their operations (*True*) or not(*False*)
$Bool_{grid\_chg}$	Indicates if the system can charge from the grid (*True*) or not (*False*)
$Bool_{BM}$	Allows participation in BM market (*True* if allowed, *False* if not)
$Bool_{DC}$	Allows participation in DC market (*True* if allowed, *False* if not)

The following equations calculate the different efficiencies as a function of the type of coupling. Eq. (2) and Eq. (3) correspond to an AC coupling of the assets:

$$\begin{cases} \eta_{so-g} = \eta_{DC-AC} \\ \eta_{w-g} = \eta_{AC-AC} \\ \eta_{st-g} = \eta_{DC-AC} \end{cases} \qquad \begin{cases} \eta_{so-st} = \eta_{DC-AC} * \eta_{AC-DC} \\ \eta_{w-st} = \eta_{AC-AC} * \eta_{AC-DC} \\ \eta_{g-st} = \eta_{AC-DC} \end{cases} \tag{2}$$

However, if the assets are DC-coupled or DC-AC coupled, the equations become:

$$\begin{cases} \eta_{so-g} = \eta_{DC-DC} * \eta_{DC-AC} \\ \eta_{w-g} = \eta_{AC-DC} * \eta_{DC-AC} \\ \eta_{st-g} = \eta_{DC-DC} * \eta_{DC-AC} \end{cases} \qquad \begin{cases} \eta_{so-st} = \eta_{DC-DC} * \eta_{DC-DC} \\ \eta_{w-st} = \eta_{AC-DC} * \eta_{DC-DC} \\ \eta_{g-st} = \eta_{AC-DC} * \eta_{DC-DC} \end{cases} \tag{3}$$

Appendix 6: Economic indicators formulations

Table 11 presents the equations for traditional indicators, along with the relevant parameters considered.

Table 11: Definition of key financial indicators. Source: [41]

Indicator	Equation	Nomenclature
NPV	$NPV = \sum_{t=0}^{N} \frac{CF_t}{(1+r)^t}$ Quantifies creation of monetary value - Profitable if NPV > 0	N: Project lifetime CF_t: Cash Flow for the year t r: Annual discount rate I: Initial investment Np: Number of years before recovering the investment $Capital_t$: Capital costs in the year t $O\&M_t$: Operation and maintenance costs in the year t F_t: Fuel costs in the year t $Carbon_t$: Carbon costs in the year t D_t: Decommissioning and waste management costs in the year t
IRR	$0 = \sum_{t=0}^{N} \frac{CF_t}{(1+IRR)^t}$ Quantifies creation of value as a rate of return - Profitable if IRR > k k: discount rate threshold	
PBP	$PBP = \frac{I}{\sum_{t=1}^{N_p} \frac{CF_t}{(1+r)^t}}$ Number of years to recover the investment - Profitable if PBP < threshold	
LCOE	$LCOE = \frac{\sum_{t=0}^{N}(Capital_t + O\&M_t + F_t + Carbon_t + D_t)(1+r)^{-t}}{\sum_{t=0}^{N} E_t\,(1+r)^{-t}}$ Assesses the unit cost of energy - Used to compare projects or technologies	
ROI	$ROI = \frac{\sum_{t=0}^{N} CF_t}{N * I} \times 100$ Ratio between average yearly cash flow and initial investment	

Appendix 7: Optimisation example

As discussed in previous sections, the algorithm optimises asset operations to maximise revenues. It evaluates the state of each energy flow every half-hour and calculates the corresponding costs or revenues. Figure 6 below illustrates the optimised operations for a day when a 100 MW storage system is co-located with a 100 MW solar farm. The model allows participation in all considered markets, and the storage system has the capability to charge from the grid. The operations are presented alongside the storage system's energy level and the corresponding electricity prices.

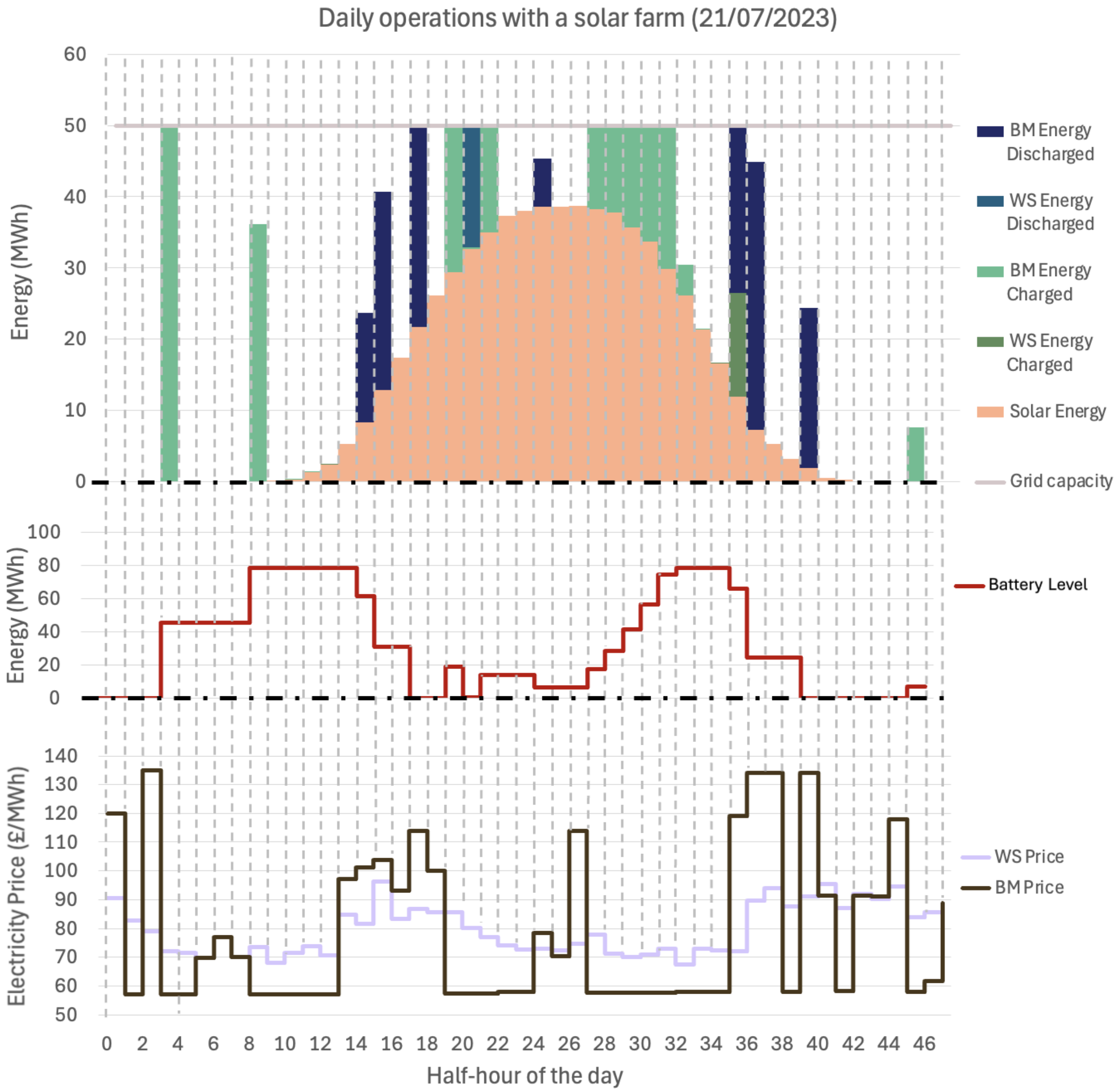
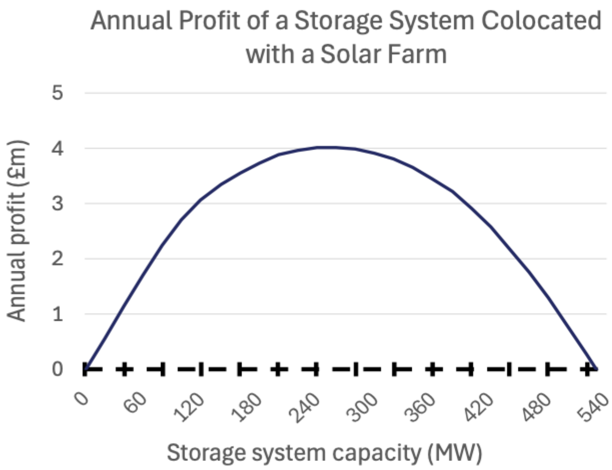


Figure 6: Daily operations of a co-located project alongside storage energy level and electricity prices

During certain time intervals, no operations occur even though they could have. This is because the storage system's daily cycles are limited to minimise degradation. It can be observed that storage discharge primarily occurs during peak hours in the morning and evening, while charging typically takes place at night and during the day when electricity prices are lower.

The sizing optimisation determines the optimal configuration by simulating the control strategy for each given capacity. The incremental approach and convex optimisation methods are applied to a storage system participating in both WS and BM markets, while charging from the grid and operating in conjunction with a 100 MW solar farm on a 100 MW grid connection. Results are outlined in Figure 7.



Indicator	Value
Yearly benefit	£13,287,100
Annualised profit	£4,035,665
NPV	£39,622,750
IRR	15.9%
PBP	7 years
Initial Grid Usage	14.9 %
Optimised Grid Usage	47.5 %

Figure 7: Annual profit for various storage system capacities co-located with a solar farm, with a table of the optimal indicators for a co-located project with a 100 MW solar farm

The optimal storage capacity is determined to be 252 MW, which maximises the annualised profit. This profit represents the yearly benefits after deducting the various annualised capital costs. The maximum annualised profit is £4,035,665 per year.

For this configuration, the two convex optimisation approaches were tested to determine the most efficient option. Figure 8 compares the optimised storage capacity and the computation times for both methods, with tolerance values ranging from 20 MW to 1 MW. Dichotomy method proves to be the faster algorithm for the sizing optimisation. Consequently, it has been used for the simulations presented in the Results section.

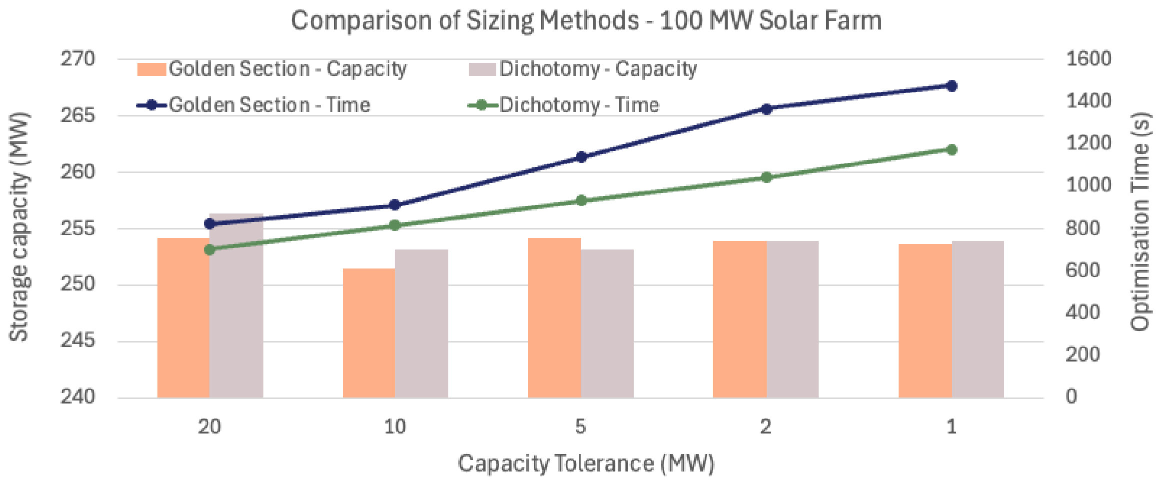


Figure 8: Comparison of optimisation methods for the storage system sizing depending on the tolerance accepted

Appendix 8: UK Results – Annual profit details for wind co-located projects

Profits for co-located projects with solar farms are discussed in detail in the main section. Figure 9 presents the profit analysis for a wind farm equipped with a 1-hour storage system, which has an optimal capacity of 168 MW. Despite a reduction in system costs, co-location with wind farms results in lower operations on the WS market, leading to a decreased total profit. However, overall patterns remain quite similar between co-located solar and wind projects.

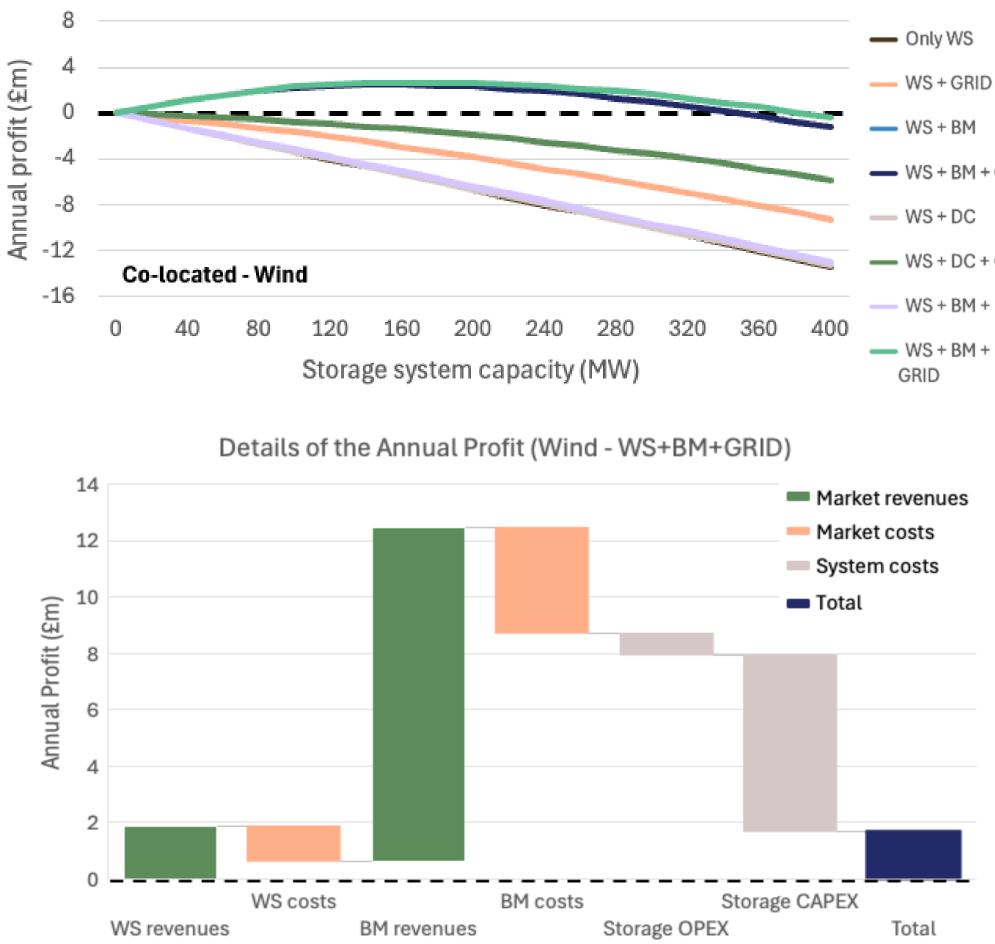


Figure 9: Annual profits for storage co-located with wind when participating in various markets. (a) Profits from each combination of markets at various capacities participations and storage capacities and (b) breakdown of revenues (from discharging) and costs (from charging) for each market at the optimal storage capacity.

Appendix 9: UK Results – Impact of the discharge duration on co-located projects with wind farms

As explained in Section **Error! Reference source not found.**, the impact of the storage s ystem's discharge duration on the economic viability of co-located projects can be analysed similarly for both solar and wind projects. Figure 10 outlines the potential profits generated by a storage system co-located with a wind farm for various capacities and discharge durations ranging from 1 to 6 hours.

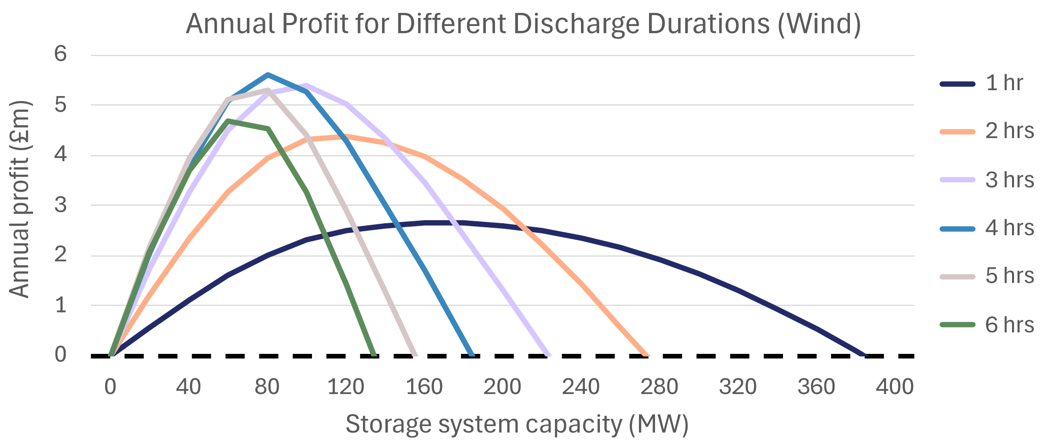


Figure 10: Annual profit for different discharge durations of the storage system when co-located with a wind farm

Figure 11 illustrates the revenues generated by a storage system with optimal power capacity for each discharge duration when co-located with a wind farm.

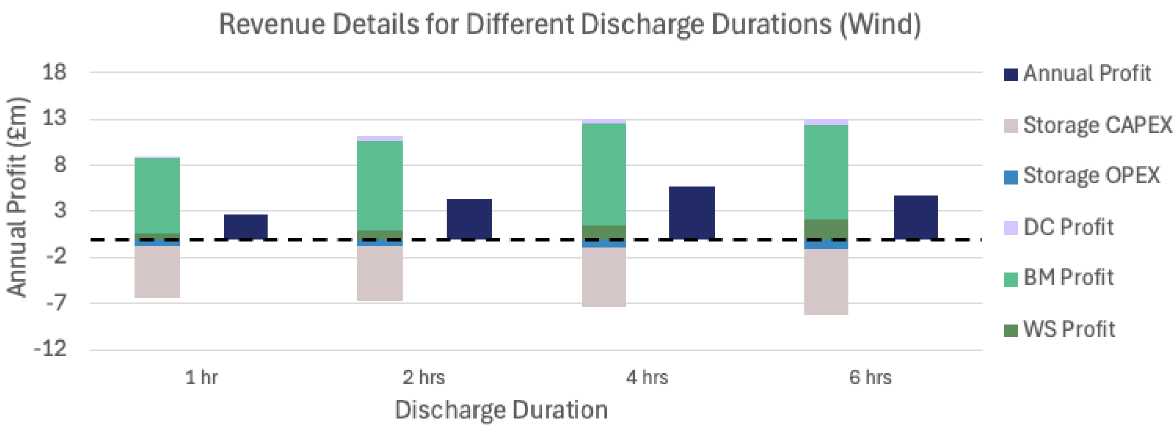


Figure 11: Annual profit details for different discharge durations of the storage system in co-location with a wind farm

Appendix 10: UK Results – Renewable-to-Grid Ratio: Complementary Analysis for Co-Located Projects

Section **Error! Reference source not found.** also discussed the optimal Renewable-to-Grid r atio for co-locating storage systems, using examples of weekly operations to demonstrate how variations in renewable energy types influence the outcomes. To validate this analysis, Table 12 and Table 13 summarise the energy flows of the storage system across different ratios, considering co-location with solar farms and wind farms, respectively.

Table 12: Energy flows of the storage system for co-located projects with a solar farm and different solar-to-grid ratios

Solar-to-Grid Ratio	WS Market		BM Market		Solar-to-Storage
	Charge (GWh)	Discharge (GWh)	Charge (GWh)	Discharge (GWh)	Charge (GWh)
0.4	28.9	33.8	150.1	137.4	0.075
1.2	25.2	28.0	123.6	115.3	0.532
2	25.6	38.2	108.1	119.8	30.6

Table 13: Energy flows of the storage system for co-located projects with a wind farm and different wind-to-grid ratios

Wind-to-Grid Ratio	WS Market		BM Market		Wind-to-Storage
	Charge (GWh)	Discharge (GWh)	Charge (GWh)	Discharge (GWh)	Charge (GWh)
0.4	27.5	34.4	117.8	107.1	0.217
1.2	14.1	18.4	77.7	69.1	1.34
2	6.95	14.0	42.9	38.5	6.32

Appendix 11: UK Results – Market Participation Scenarios for Full Hybrid Projects with Wind Farm

While Section **Error! Reference source not found.** analyses the impact of multiple market p articipation on the annual profit of full hybrid projects, it primarily focuses on solar farms. Figure 12 presents the annual profit for full hybrid projects co-located with a wind farm, revealing a similar pattern to that of solar projects, but with higher generated profits.

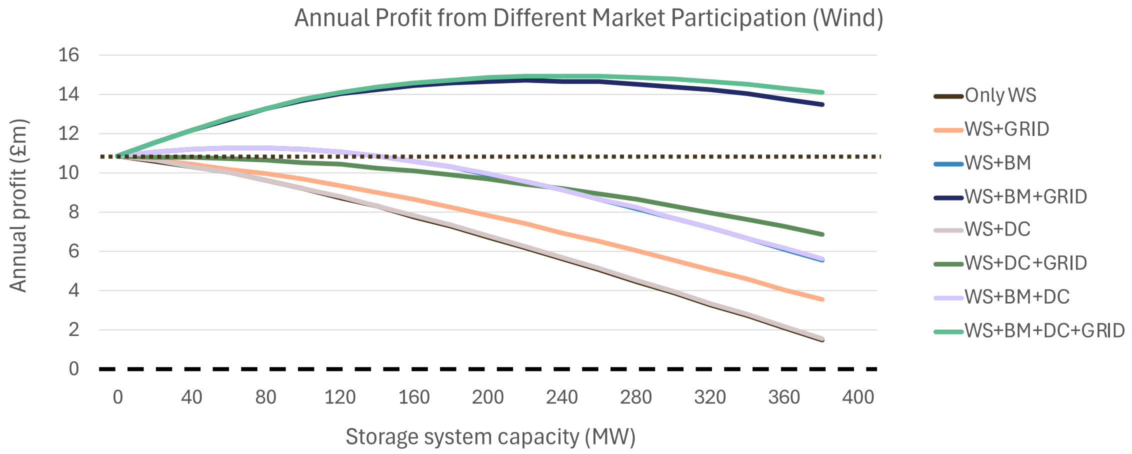


Figure 12: Annual profit computation for different market participation – Full hybrid projects with a wind farm

Appendix 12: UK Results – Impact of the Location: North and South Site Selection

This section evaluates how asset location affects optimisation results, particularly the impact of the renewable asset's capacity factor on storage system sizing and economic indicators. Two UK sites were selected to isolate location effects: one in the south and the other in the north. Table 14 and Figure 13 outline their key characteristics and a map of the locations.

Table 14: Characteristics of selected sites for the study of the location impact.

	South	North
Location Name	Eveley Farm	Milltown Solar Farm
Latitude; Longitude	51.098; -1.533	57.673; -3.235
Altitude (m)	76	6
2023 Solar Capacity Factor	15.6%	13.4%
2023 Wind Capacity Factor	37.5%	39.5%

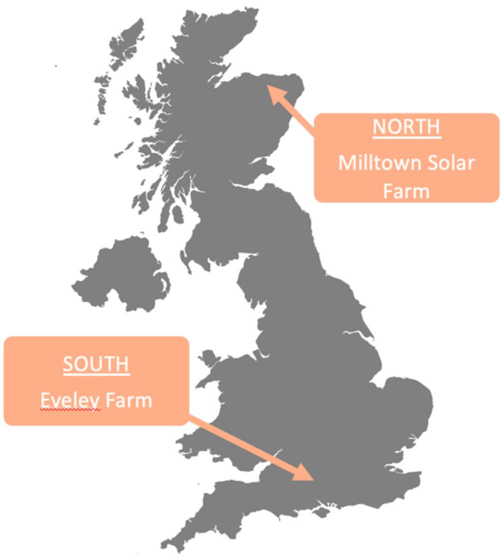


Figure 13: UK location for the two sites considered in the study of the location impact.

Solar farms have a higher capacity factor in the south, while wind farms perform better in the north, with a noticeable 2% difference for both types. Simulations determined the optimal storage capacity for a 100 MW renewable asset and grid connection, analysing both Co-located and Full Hybrid projects. Figure 14 presents results for both solar and wind scenarios.

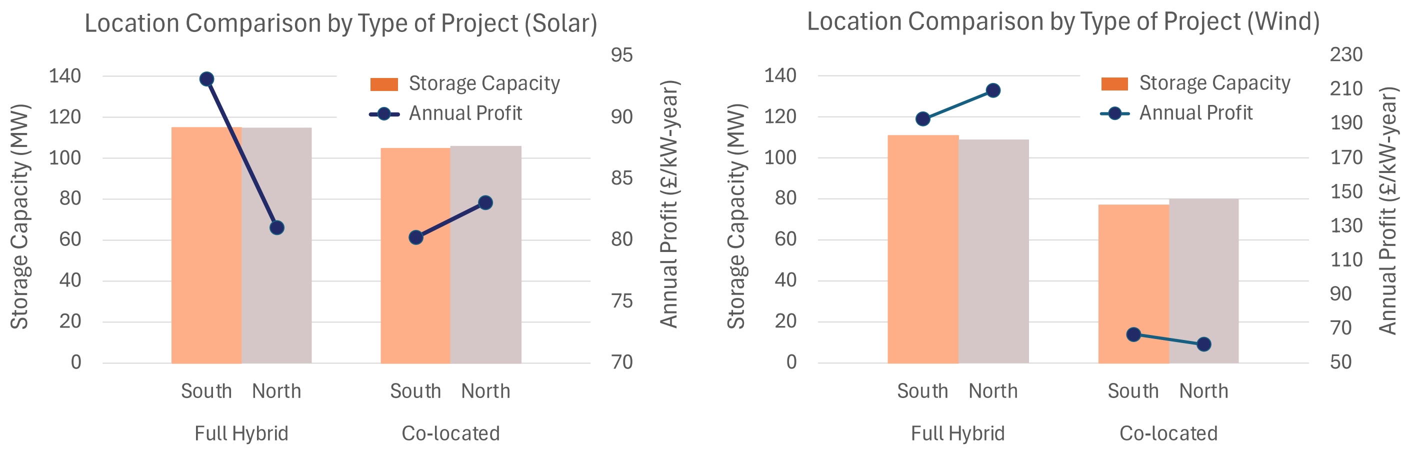


Figure 14: Optimal storage capacities and corresponding profits for the two locations, the two types of projects and the two renewable asset types

For both renewable assets, we observe contrasting outcomes between a Full Hybrid and a Co-located project. In a solar project, the Full Hybrid model generates higher profits in the southern regions of the country. Conversely, a storage developer maximises own profits in the north. The profit difference is more pronounced in Full Hybrid projects, especially for solar farms.

Table 15 and Table 16 present the initial and optimal indicators for Full Hybrid projects located in the southern and northern regions of the country, respectively for solar farms and wind farms.

Table 15: Comparison of indicators for stand-alone solar farms and full hybrid projects

	Stand-alone solar farm indicators		**Full hybrid project Indicators**	
	South	**North**	**South**	**North**
IRR	9.22%	6.86%	16.5%	15.5%
NPV	£8,152,000	-£7,350,500	£105,199,000	£91,562,000
PBP	15	21	7	8
Capture Rate	93.9%	93.0%	97.3%	96%
Grid Usage	15.2%	12.8%	62.0%	61.1%

Table 16: Comparison of indicators for stand-alone wind farms and full hybrid projects

	Stand-alone wind farm indicators		Full hybrid indicators	
	South	**North**	**South**	**North**
IRR	20.4%	21.8%	20.9%	21.8%
NPV	£136,792,000	£152,959,000	£210,185,000	£224,267,000
PBP	6	6	6	6
Capture Rate	96.8%	102.4%	100.7%	106.3%
Grid Usage	39.0%	38.8%	72.9%	72.7%

Appendix 13: International Results – List of studied countries

Table 17 to Table 20 list the states and countries included in the global analysis of hybrid project potential, with statistics on the wholesale market price, the mean intra-daily spread in prices, and the range of mean annual wind and solar capacity factors (min-max), all during 2023. The currency for all wholesale prices was converted to GBP using the year-average market exchange rates (GBP 1 = 1.89 AUD = 1.27 USD = 1.16 EUR = 189 JPY). The geographical coordinates and capacity factors for all 252 modelled locations are given as a supplementary data file: `site_metadata.csv`.

Table 17: List of power markets studied in Europe, giving the mean wholesale price, the mean difference between maximum and minimum daily wholesale price, and the range of capacity factors for wind and solar (showing 1 standard deviation either side of the mean across the sites simulated within each market).

		Wholesale price (£/MWh)		Capacity factors	
Name	**Code**	**Mean**	**Daily spread**	**Wind**	**Solar**
Austria	AT	87.84	77.99	15.3-37.5%	15.2-16.2%
Belgium	BE	83.40	77.60	30.9-56.2%	14.1-15.6%
Bulgaria	BG	89.77	108.16	12.1-39.8%	18.1-19.4%
Cyprus	CH	92.32	54.51	5.7-19.2%	17.3-17.4%
Czechia	CZ	86.30	80.67	27.2-30.8%	14.4-16.7%
Denmark	DK	72.12	80.21	36.1-56.8%	13.1-15.1%
Estonia	EE	77.83	104.2	37.2-40.9%	13.2-13.7%
Finland	FI	48.11	65.57	23.4-30.5%	10.4-12.2%
France	FR	83.13	71.72	24.5-34.7%	15.4-18.7%
Germany	DE	81.58	83.54	22.9-34.0%	13.4-15.5%
Great Britain	GB	93.56	81.80	34.3-49.8%	11.8-14.6%
Greece	GR	103.11	100.76	19.1-46.1%	17.9-22.3%
Hungary	HR	89.21	91.14	24.6-29.9%	16.5-17.8%
Ireland	IE	103.57	73.88	38.9-47.5%	12.0-13.1%
Italy	IT	109.88	65.67	23.3-35.5%	18.0-20.6%
Latvia	LV	80.59	103.44	26.2-37.4%	12.9-13.3%
Lithuania	LT	81.09	103.85	18.7-32.9%	12.9-13.4%
Netherlands	NL	81.97	91.60	37.0-37.9%	13.6-14.1%
Norway	NO	50.73	29.67	29.8-42.3%	7.9-11.5%
Poland	PL	95.96	61.48	22.7-31.7%	13.5-14.4%
Portugal	PT	77.58	58.74	27.3-43.1%	18.2-21.0%
Romania	RO	89.63	108.72	22.5-36.3%	15.8-17.3%
Serbia	RS	89.15	84.22	26.9-31.2%	16.3-16.9%
Slovakia	SK	90.08	86.09	24.0-35.4%	15.2-15.9%
Slovenia	SI	89.41	82.88	23.3-23.7%	16.3-16.7%
Spain	ES	77.15	61.26	26.9-40.7%	19.2-21.2%
Sweden	SE	44.61	52.73	21.6-26.7%	11.4-13.1%

Table 18: List of power markets studied in the United States, following the same conventions as Table 17.

		Wholesale price (£/MWh)		Capacity factors	
Name	**Code**	**Mean**	**Daily spread**	**Wind**	**Solar**
California	CAISO	46.92	59.67	18.8–27.4%	21.4–23.8%
Texas	ERCOT	44.01	174.35	30.7–41.8%	20.3–23.2%
Midcontinent	MISO	22.80	21.04	27.4–40.9%	18.6–20.4%
New York	NYISO	24.04	19.77	22.9–31.9%	16.5–18.8%
Mid Atlantic	PJM	23.96	26.06	21.8–31.2%	19.0–20.2%

Table 19: List of power markets studied in Australia, following the same conventions as Table 17.

		Wholesale price (£/MWh)		Capacity factors	
Name	**Code**	**Mean**	**Daily spread**	**Wind**	**Solar**
New South Wales	NSW	50.85	211.31	25.1–33.3%	21.6–23.3%
Queensland	QLD	48.05	258.96	22.3–35.2%	22.4–23.3%
South Australia	SA	42.44	287.99	36.0–45.1%	20.4–22.7%
Tasmania	TAS	29.54	75.28	35.6–47.3%	16.9–20.2%
Victoria	VIC	29.03	133.63	23.1–42.1%	18.7–21.3%

Table 20: List of power markets studied in Japan, following the same conventions as Table 17. Only one location was simulated per market zone, hence only the mean capacity factors are given. The Hokuriku power market was merged into Chubu and Kansai due to its small size; its power prices were almost perfectly correlated (R^2 > 0.99) and it contains few large solar farms (and no wind farms).

		Wholesale price (£/MWh)		Capacity factors	
Name	**Code**	**Mean**	**Daily spread**	**Wind**	**Solar**
Chubu	CB	65.84	65.86	14.5%	20.4%
Chugoku	CG	58.46	68.62	26.1%	18.5%
Hokkaido	HK	66.93	64.62	26.3%	17.0%
Kansai	KS	58.76	68.31	25.5%	18.8%
Kyushu	KY	53.87	75.63	19.7%	19.2%
Shikoku	SK	57.69	70.58	26.3%	19.4%
Tohoku	TH	66.64	62.98	25.4%	16.4%
Tokyo	TK	71.15	53.88	23.2%	18.7%

Appendix 14: Regional case studies

This section examines five regions with notable variations in hybrid project potential: Sweden, the UK, New South Wales (Australia), ERCOT (US), and PJM (US). Table 21 presents key market and production indicators for these areas.

Table 21: Production indicators and electricity market characteristics in chosen regions

	Sweden	UK	NSW, AUS	ERCOT, US	PJM, US
Average WS Market Price (£/MWh)	44.44	93.57	50.92	55.92	30.32
Average Price Spread (£/MWh)	28.87	40.25	104.7	213.4	14.77
Proportion of negative prices (%)	4.3	2.4	6.0	0	0
Solar Capacity Factor (%)	13.2	15.2	22.4	21.4	19.9
Wind Capacity Factor (%)	20.9	36.0	30.7	36.0	24.5
Solar Capture Rate (%)	95.5	93.7	72.9	120.3	106.8
Wind Capture Rate (%)	88.2	96.4	105.4	63.8	101.2
Grid Usage (%) - Solar	12.95	14.9	22.0	21.0	19.6
Grid Usage (%) - Wind	20.5	35.3	30.1	35.3	24.0

Regional differences are significant, with varying market prices and energy availability. For instance, Australia frequently sees negative prices, while US regions do not. Solar capacity factors range from 13.2% to 22.4%, affecting grid usage and capture rates. Table 22 provides a summary of the results found in Sections **Error! Reference source not found.** and **Error! Reference source not found.** specifically for these 5 areas.

Table 22: Summary of findings from international simulations for the case study regions

	Sweden	UK	NSW, AUS	ERCOT, US	PJM, US
Full Hybrid project – Storage Optimisation					
Storage Capacity (MW)	0	0	120	120	0
Discharge Duration (hr)	4	4	2	4	4
Max. Storage CAPEX (£/MW)	260,000	440,000	940,000	1,380,000	100,000
Full Hybrid project – Renewable Optimisation					
Solar Capacity (MW)	0	197	0	102	0
Wind Capacity (MW)	0	192	0	0	0
Market for PV+WIND+BESS	Storage Only	PV+WIND +BESS	Storage Only	PV+BESS	Storage Only
Min. RES Fixed Price (£/MWh)	90	40	40	30	80
Co-located project – Renewable Optimisation					
Solar Capacity (MW)	150	150	0	50	150
Wind Capacity (MW)	50	0	0	0	50

For storage developers, co-locating with solar farms is viable in most regions, but wind co-location is less favourable except in Sweden and PJM, particularly when the renewable-to-grid ratio is low.

New South Wales and Texas are strong candidates for Full Hybrid project development compared to stand-alone renewable farms. However, in Australia, developers should prioritise stand-alone storage systems. In the US, Full Hybrid projects are beneficial with solar farms, but stand-alone storage is preferable for wind energy. In the UK, Full Hybrid projects present a promising opportunity for enhancing storage system revenues.

Figure 15 and Figure 16 illustrate energy flows and profit distribution in Full Hybrid projects with a 4-hour storage system and 100 MW solar asset. Energy traded correlates with regional price spreads, with negative prices impacting dynamics. For instance, ERCOT has a high price spread but less energy exchanged due to its lack of negative prices, unlike the UK.

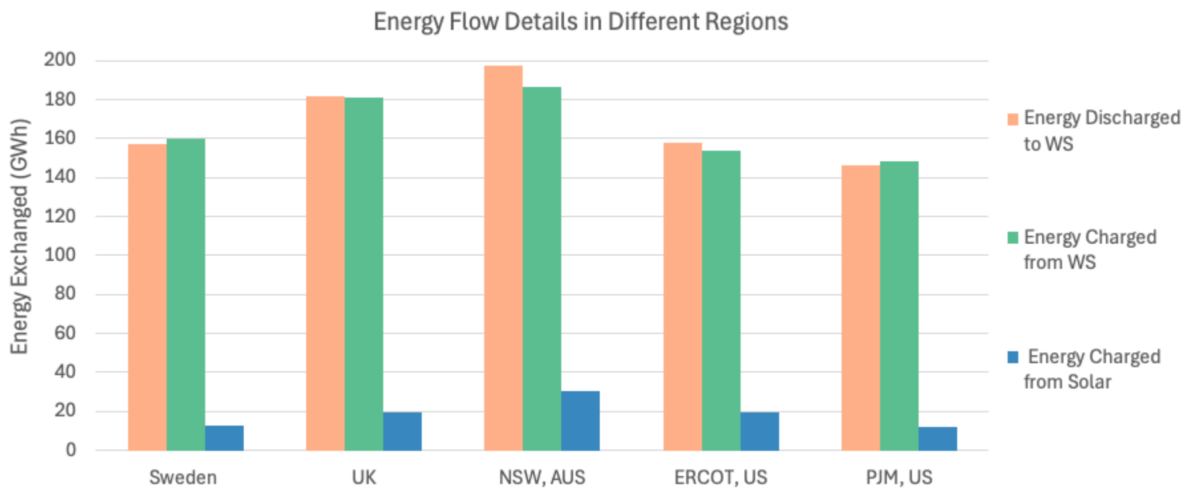


Figure 15: Energy flows of the storage system in solar full hybrid projects for each region

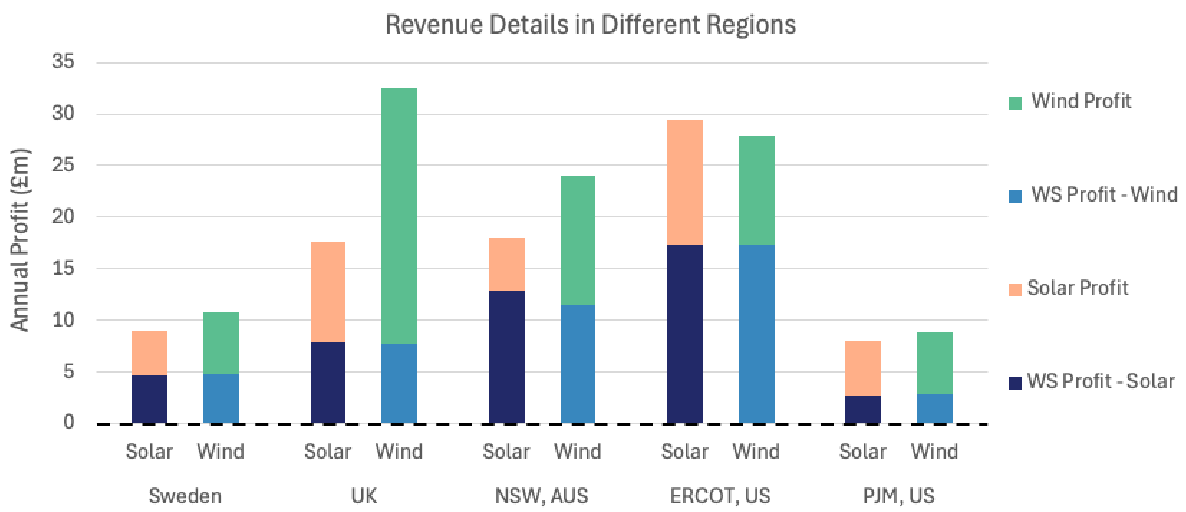


Figure 16: Repartition of profits between storage and renewables in full hybrid projects

Energy charged from solar varies by region. For example, only 7% of solar energy is stored in PJM, while 15.5% is stored in Australia. Higher solar capture rates typically mean less energy is stored, especially when price spreads are unfavourable. Conversely, Australia benefits from storage due to a high price spread and low capture rate, highlighting the region's hybrid project potential.

On average, adding a storage system boosts the capture rate by 4.6%, varying by region. Solar farms in PJM see a 2.7% increase, while ERCOT experiences a 9.8% rise. The storage system also enhances grid usage, with solar projects increasing by 31.6% and wind by 28.1% across all regions.

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