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The economic impact of location on a solar farm co-located with energy storage

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ABSTRACT

Deploying energy storage (ES), alongside renewable generation, can help to decarbonise electricity grids. A key aspect of deploying these is choosing a suitable location, which is both geographically feasible and economical. Previous studies identify locations with suitable geographies; here we focus on the economic impact of location. We explore how the maximised profits, determined using a mixed integer linear programming (MILP) optimisation model, of a solar farm co-located with ES vary in different regions around Great Britain (GB) as a case study. We perform a cost–benefit analysis from the point of view of a distribution-connected solar farm owner. Real solar generation data is used, along with a weather model, to accurately represent forecast and actual output. For solar farms without ES profits are higher in locations with greater solar irradiance. However for sites with ES we find greater profit variation, primarily due to different distribution charges. For the majority of GB, ES does not add sufficient value to offset its high upfront costs and is not worth adding to solar sites. Additionally, it is found to be uneconomical to add ES to most existing solar farms, despite many studies highlighting the grid benefits this would bring. We recommend that distribution network operator and market pricing better reflects the value which ES can bring to the electricity system economical to add to solar sites. To encourage increased co-location distribution operators should offer greater a differential between non-intermittent generation and intermittent generation payments, in particular at times of high system demand.

1. Introduction

1.1. Overview

Climate change is a major geopolitical issue, and the transition from fossil fuels to renewables is crucial [1]. Solar photovoltaics (PV) are a key component of this transition, accounting for 11% of renewable electricity generation in the UK [2]. Energy storage (ES) is also important, as it can mitigate fluctuations in renewable output and enable optimal use of variable electricity sources [3–5].

ES can be economically beneficial for renewable generators and grid operators by creating value through energy arbitrage and lowering system costs [6].

Co-locating ES alongside renewables can also provide additional benefits such as attractive economics, improved operation, and reduced power curtailment. In this work, we explore the economic impact of location on solar PV farms co-located with ES in Great Britain, to assess the feasibility of deploying ES under current market conditions. Whilst ES does not necessarily need to be co-located alongside renewable generation to reap aforementioned grid benefits, there are other unique advantages to co-location. These include attractive economics, through shared inverters and grid connection costs, and improved operation, such as the battery capturing clipped power that may otherwise be lost [7,8]. Co-locating ES alongside renewables can also reduce power curtailment [9].

In this work we will explore the economic impact of location on solar PV farms co-located with ES across Great Britain (GB). We will calculate the maximum obtainable income with and without ES, and hence the value it can bring. The aim is to study how feasible it is to deploy ES, particularly alongside solar PV, since previous work has shown how important this for decarbonisation, improving power quality and reducing grid system costs. The following section will explore literature on the topic of optimising the location of solar farms and the scheduling of co-located ES and solar.

1.2. Literature review

The optimal choice of location for solar farms is a research area currently receiving a great deal of attention, for example [10–17].

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Nomenclature

The abbreviations and symbols used are defined as follows:

Abbreviations

ES	Energy storage
PV	Photovoltaic
DNO	District network operator
$MILP$	Mixed integer linear programming
NPV	Net present value

Indices

t, t'	Time (hour)
n	Solar site
r	DNO regions
y	Year

Sets

T	Set of time/periods (hours)
N	Set of solar sites
R	Set of DNO regions in the UK
Y	Set of years of project lifetime

Parameters

η_n^c	Charge efficiency of energy storage device at solar site n
η_n^d	Discharge efficiency of energy storage device at solar site n
μ_{rn}	1 if solar site n is located in DNO region r, 0 otherwise
$\bar{P}_n$	Maximum power of energy storage device at solar site n (MW)
p_t^{BM}	Price of electricity in the balancing market at time t (£/MWh)
$\hat{p}_t^{BM}$	Predicted price of electricity in the balancing market at time t (£/MWh)
$\hat{p}_t^{DA}$	Predicted price of electricity in the day-ahead market at time t (£/MWh)
p_{rt}^{DNO}	Charges for DNO region r at time t (£/MWh)
S_{nt}	Actual solar output power from site n at time t (MW)
$\hat{S}_{nt}$	Predicted solar output power from site n at time t (MW)
$X_{n,0}$	Initial capacity of energy storage device in site n at time $t = 0$ (MWh)
$\bar{X}_n$	Maximum capacity of energy storage device in site n (MWh)
$\underline{X}_n$	Minimum capacity of energy storage device in site n (MWh)
C_n^i	Installation cost of energy storage in site n (£)
C_{ny}^m	Yearly maintenance cost of energy storage in site n (£)
C^{SB}	Energy storage block cost (£/kWh)
C^{BOS}	Energy storage balance of system cost (£/kWh)
C^{CC}	Energy storage construction and commissioning cost (£/kWh)
C^{SI}	Energy storage integration cost (£/kWh)
C^{PD}	Energy storage project development cost (£/kWh)
C^{PE}	Energy storage power equipment cost (£/kW)
C^{COMS}	Energy storage controls and communication cost (£/kW)
C^{GI}	Energy storage grid integration cost (£/kW)
C_y^{OMV}	Energy storage yearly variable operation and maintenance cost (£/kWh)
C^{OMF}	Energy storage yearly fixed operation and maintenance cost (£/kWh-year)
NPV_n	Net present value of energy storage in site n (£)
I_{ny}	Yearly total income of energy storage in site n (£)
I_{ny}^{DA}	Yearly day-ahead income of energy storage in site n (£)
I_{ny}^{DNO}	Yearly DNO income of energy storage in site n (£)
I_{ny}^{BM}	Yearly balancing market income of energy storage in site n (£)
R_n	Residual value of energy storage after project lifetime in site n (£)
d	Net present value discount rate
a	Acceleration of depreciation

Continuous variables

P_{nt}^c	Charging power of energy storage device in solar site n at time t
P_{nt}^d	Discharging power of energy storage device in solar site n at time t
P_{nt}^{exp}	Power exported to grid from solar site n at time t in the day-ahead market
$\hat{P}_{nt}^{exp}$	Power exported to grid from solar site n at time t in real time
X_{nt}	Capacity of energy storage device in site n at time t

These studies can be broadly split up into two categories: those that consider location within an electrical network, and those that consider geographical location. The first category optimises locations of power-grid connections, to reduce power losses and improve voltage profile [10,11], the latter of which presents a novel algorithm to improve system performance, and to minimise connection costs [12]. These studies are valuable from purely a grid point-of-view; however, they do not consider factors such as geography, weather and socio-economics, which may vary regionally and affect optimal choice of location.

In the second category, the studies look at large areas; for instance, the authors of [13,14] study the optimal locations of PV in Brazil and PV–wind hybrid in Iran, respectively. Both use Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) to rank locations according to factors such as climate, environment, geography and economics. Other papers using similar ranking methods include [15,16], which study the deployment of solar farms in India and Bali, respectively. In [17], the authors use GIS analysis to identify suitable locations for solar farms in the UK; they find that by not considering local planning permission and grid constraints, area overestimations may occur up to 97%.

Few studies have explored the optimal location for solar PV farms co-located with energy storage (ES), with most focusing solely on solar.

Some studies, such as [18,19], consider network connection optimisation rather than geographical location. Another study, [20], models the performance of solar and molten salt storage in three locations in Egypt. However, these studies are limited in scope and do not consider differences in geography or weather. Studies such as [21,22] explore the optimal battery size in different locations but only on a small scale. It is important to investigate the impact of location on a larger scale, considering numerous possible sites throughout the country.

Recent developments in energy storage (ES) technology are important for optimising the location of ES with solar. Reviews on ES technologies, such as [23,24], should be taken into account. Lithium ion batteries are found to be more efficient than lead acid and flow batteries, with flow batteries having the greatest number of cycles. Costs of lithium iron phosphate, lithium nickel manganese cobalt oxide, and lead acid batteries are similar, with LFP being slightly more economical. Redox flow batteries are less economical. Whilst this study focuses on co-located battery storage with solar, it should be noted that the methodology can be applied to other types of storage.

Optimised ES scheduling is crucial to maximise profits for the solar co-located site. Mixed Integer Linear Programming (MILP) and Convex Optimisation (CO) algorithms are used in [25,26] to minimise the electricity bills of consumers on particular tariffs with access to solar and storage. Larger grid-scale systems with access to wholesale markets, as considered in this work, are studied in [27,28]. The latter uses a Model Predictive Control (MPC) algorithm to optimise ES in day-ahead and real-time wholesale markets. Other studies expand upon these by including market uncertainties [29,30] and battery degradation [31,32]. However these studies do not consider batteries co-located with solar. In [33] they optimise the economics of lithium ion and lead acid batteries co-located with grid connected solar with consideration of degradation. They find that the levelised cost of energy and net present cost of energy are lower for the lead acid battery, suggesting that this is the more economical battery chemistry to use in combination with grid connected solar.

Finally, there are several methods for calculating the value added by ES (in this case, by co-locating it with solar); these can be split into different categories. In [33–35] they present a Net Present Value (NPV) analysis to assess the value of ES performing arbitrage and different batteries in distribution substations, respectively. On the other hand, [33,36] present methods to calculate Levelised Cost of Storage/Energy (LCOS/LCOE), respectively, in order to compare the effects of different technical characteristics of ES on its economics. Another method to assess the value of storage is Real Options (RO) analysis, as considered in [37–39]. Since NPV is the most ubiquitous method, it will be used here.

1.3. Locational factors GB

The criteria for solar farm site suitability in the UK is presented in [17]; these are geographical (including land slope), weather related and constraints due to network connections. Since this work is interested in identifying the optimal region, which will be a large area rather than a specific site, finer details such as distance from network connections, rivers, woodland and urban areas will be omitted. Additionally, as the aim is to find the region where profits can be maximised only factors affecting this will be considered. These are:

- Weather - Solar irradiance and cloud cover will affect solar farm power output, and hence total income made through selling this in wholesale markets.
- Regional Electricity Grid Charges - These are outlined subsequently and will also affect the total income.

In common with other countries, in GB there are a number (14) of licensed DNOs (Distribution Network Operators), illustrated in Fig. 1, which are responsible for the distribution of electricity around a particular region of the national grid. These are operated independently and hence each DNO may impose a different set of charges on the distribution grid users, which may be consumers or generators. This is particularly important because a solar farm may face different charges for exporting power depending on which DNO region it is located in [40].

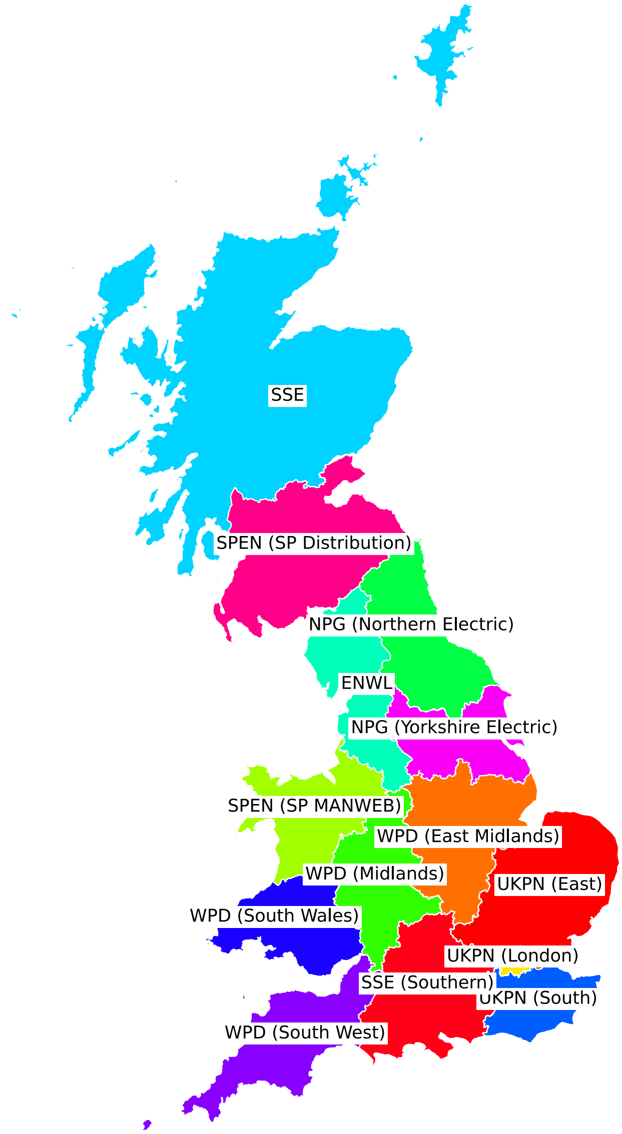


Fig. 1. Map showing the 14 different DNOs and their regions in GB.

Information on Use-of-System charges imposed by each DNO can be found on their websites [41–46]. Negative charges are given to generators for exporting power to the distribution networks, with intermittent generators receiving a set payment and non-intermittent generators receiving varying payments following a red, amber, and green charging structure. Fig. 2 shows this for Western Power Distribution (East Midlands). It should be noted that at weekends these payment structures differ slightly: there are normally no red time bands. Weekly time series of payments were generated for each DNO, considering the full weekly structures.

In Fig. 3 the payments received by the different generator types are shown for the different DNO regions. It can be seen that there is a distinct difference between the payments received in the different regions for both intermittent and non-intermittent generators. Additionally, the mean payments received by non-intermittent generators is greater than for intermittent, and the red time band payments are significantly

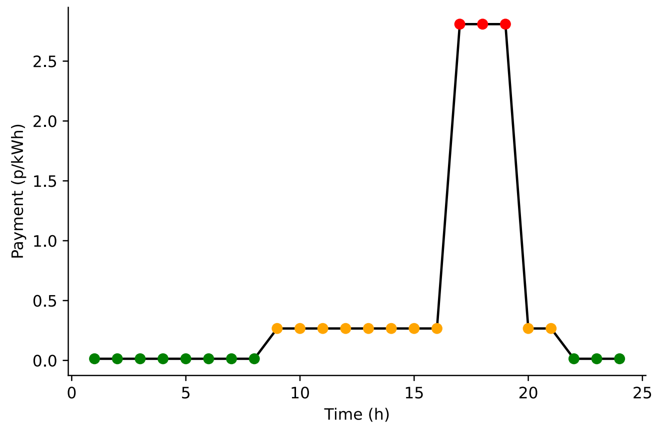


Fig. 2. Red, amber and green time bands for Western Power Distribution (East Midlands).

greater. Since ES is defined as non-intermittent [47], by co-locating storage with solar the red payment band can be taken advantage of.

1.4. Contributions of this work

This work builds upon grid scale battery storage optimisation models in the literature, such as [28], and co-located with solar, in as [33]. Whilst many research papers have answered the question - what is the best way to use batteries to generate revenue? Far fewer papers have considered - where is the best location to locate a battery to generate revenue? Yet, location is an important factor to consider when it comes to practically deploying these devices.

Novelty lies within the exploration of how the battery's economics varies with its location on country-wide scale. This work addresses a gap in the literature - previous studies optimising the location of solar with battery storage are few and far between, and limited to a local scale, or else limited to a small number of possible locations. It brings together two important deployment considerations usually studied separately: economics and location. Another key strength is that the model can easily be replicated and applied to different case studies, making it a useful tool for decision-making for battery storage projects. Additionally, it has implications that are important to solar farm owners and investors interested in this technology, and policy-makers wishing to predict the future solar-storage landscape. The novel contributions of this work are as follows:

- This study will explore the economic impact of location on solar co-located with storage on a large, country-wide scale considering a large number of possible sites. Specifically, it studies Great Britain (GB) using historical solar generation data and corresponding market price data from 2016–2017, with locational charging prices from the most recently available reports (2020–2021).
- A novel MILP optimisation model is introduced to determine the scheduling of ES with solar which maximises profits in day-ahead and balancing markets, whilst considering location dependent distribution grid charges. This is a non-deterministic model with solar output and market prices unknown ahead of time.
- The locational study will examine the effects of changing ES size (maximum power and capacity rating) on its NPV in different regions, to determine optimal size to maximise value.

The rest of this paper is structure as follows: Section 2 presents the methodology, this includes prediction models for solar output and market prices, as well as the MILP optimisation model; Section 3 presents the results and discussion; finally, Section 4 presents the conclusions and future work.

2. Methodology

In this section we firstly outline the source and manipulation of the solar data, and the weather model applied to predict solar generation. Then we discuss electricity markets in Great Britain and the methods employed to predict prices. Next, we present models to optimise co-located ES revenues in the day-ahead and real-time markets. Finally, we outline how we determined the economic feasibility of installing ES in each location.

2.1. Solar sites

Data regarding 150 solar panel sites in GB has been provided for this work [48]. The data set contains information about location, size and hourly generation (from 2016–2017) for each site. For this work each of these solar sites is scaled up to have the same maximum power output (1 MW - as this is representative of a distribution connected solar farm [49]) so that direct comparisons between sites can be made. The co-located ES will be smaller than the maximum solar output, since

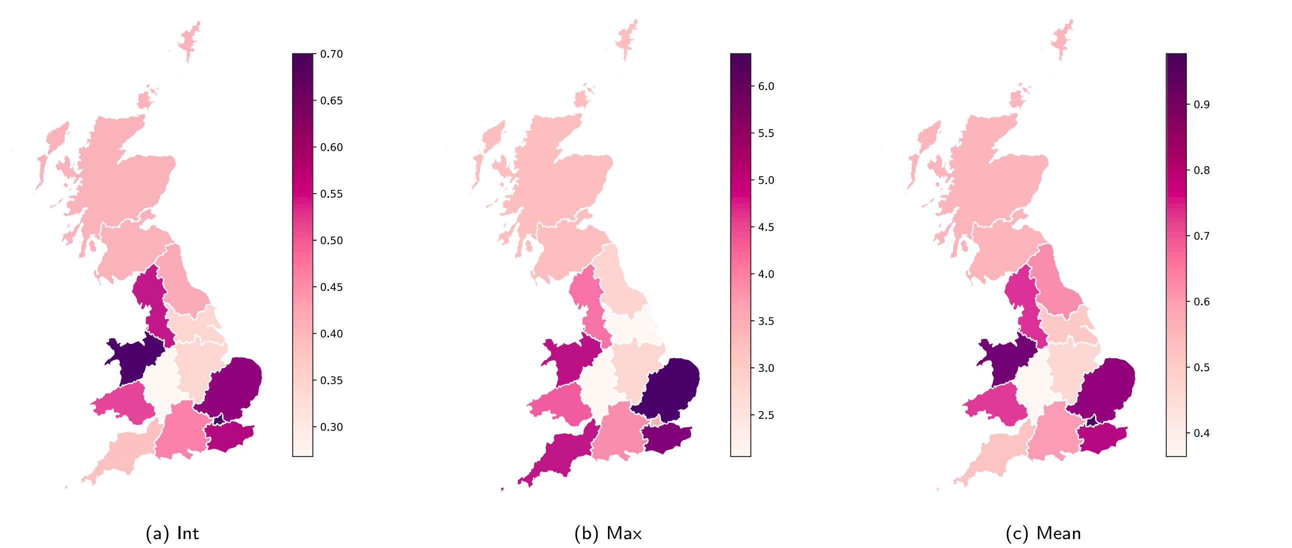


Fig. 3. DNO payments (p/kWh) for intermittent generators (Int), non-intermittent generators red band (Non-Int Max) and non-intermittent generators mean (Non-Int Mean).

average yearly solar in GB has a load factor of 0.112 [2]. Preliminary analysis of solar data suggests that the storage should be sized on the order 10^{-1} MW for a 1 MW sized solar farm.

In [50] a weather model is developed and used to predict hourly solar generation for each of these sites using information about their location, size and elevation. It uses a Gradient Boosted Tree machine learning model (based on methods in [51,52]) that was trained using historical weather forecast and solar outturn data to forecast solar outturn and, therefore, solar PV generation at different sites in the UK. The weather forecast data included irradiance, air temperature, humidity, wind speed, and wind direction (data from the European Centre for Medium-Range Weather Forecasts [53]). It was found that including all of these variables improved accuracy. The model also considered time of day, year, and solar geometry, as well as time-lagged variables to improve performance further.

2.2. Electricity markets

Energy trading can occur bilaterally or on exchanges. A bilateral contract is an agreement between two parties (eg. a supplier and generator) to exchange energy under a set of specified conditions [54]. These are difficult to model as data is not readily available. In GB the two main exchanges are European Power Exchange and Nord Pool (N2EX) where electricity can be traded for next day delivery and usage [55]. Within each of these exchanges electricity can be sold in a day-ahead auction market (which closes one day ahead of delivery at 9:50 am UK time), or an intra-day market (where trading occurs continuously up to one hour before delivery). The day-ahead market is much more liquid than the intra-day market, which means that market price is more likely to reflect intrinsic value [56]. Additionally, prices are less volatile in the day-ahead market, hence this is less risky for participants to trade in and will be considered here rather than the intra-day market.

In real-time, it is up to National Grid to balance supply and demand on a second-by-second basis. It does so by accepting offers (generation increases and demand reductions) and bids (generation reductions and demand increases) made in near real-time. This is referred to as the Balancing Mechanism. Balancing Mechanism trading is performed in half hourly intervals and market closure to submit bids/offers is 30 minutes before the start of each interval. For a solar generator that has sold its predicted output in the day-ahead market, it must settle any discrepancies in actual output in the balancing market.

When solar is co-located with ES there is the option to shift energy trading to times when prices are more advantageous; the optimisation procedure to maximise profits through this means is presented in the following section. Since market prices are not known in advance, they must be predicted. Day-ahead market prices generally follow a certain daily pattern and hence can be predicted reasonably accurately using a simple 7-day rolling average method. The MAPE (Mean Absolute Percentage Error) for this method using N2EX data from 2016 to 2018 was found to be 11% [57]. Balancing market prices are very difficult to predict. Some studies in the literature use SARIMA (Seasonal Auto-regressive Integrated Moving Average) models [58,59]. However, when this was tested on National Grid's Balancing Mechanism it did not perform well [60]. A SARIMA(2,1,2)(0,1,2,24)[1] model was found to give an RMSE (Root Mean Squared Error) of 99.7, whereas simply using the same predictions as for the day-ahead market gave an RMSE of 34.4. It is not unreasonable to assume that these two markets will follow similar patterns, since hours with greater electricity demand (and hence higher prices) may be more likely to have greater discrepancies in real-time. Hence, the 7-day rolling average day-ahead values were used as predicted prices for both markets.

[1] Other SARIMA models were tested on September 2016 data however this one was chosen as it had the lowest AIC (Alkaike Information Criterion) value.

2.3. Day-ahead optimisation model

This section presents the MILP optimisation model used to maximise the day-ahead profits of ES co-located with solar in GB, with consideration of local DNO pricing structures. The equations governing the MILP are outlined as follows. Eqs. (1) and (2) ensure that the power used to charge/discharge each ES, n, at time, t, does not exceed its maximum limit.

$$0 \le P^{c}_{nt} \le \bar{P}_{n} \qquad \forall\, n, t \tag{1}$$

$$0 \le P^{d}_{nt} \le \bar{P}_{n} \qquad \forall\, n, t \tag{2}$$

The capacity of each ES at the end of time period, t, is described by Eq. (3); it depends upon the capacity at the end of time period $t-1$, plus/minus the effects of charging/discharging in the current time period. Eq. (4) maintains capacity within its maximum and minimum limits, and Eq. (5) states that charging power may not exceed predicted solar output power.

$$X_{nt} = X_{n,t-1} + \eta^{c}_{n} P^{c}_{nt} - \frac{P^{d}_{nt}}{\eta^{d}_{n}} \qquad \forall\, n, t \tag{3}$$

$$\underline{X}_{n} \le X_{nt} \le \bar{X}_{n} \qquad \forall\, n, t \tag{4}$$

$$P^{c}_{nt} \le \hat{S}_{nt} \qquad \forall\, n, t \tag{5}$$

Power exported to the grid is described by Eq. (6), and is equal to predicted solar output, minus ES charging and plus ES discharging.

$$\hat{P}^{exp}_{nt} = \hat{S}_{nt} - P^{c}_{nt} + P^{d}_{nt} \qquad \forall\, n, t \tag{6}$$

Finally, the objective function is given by Eq. (7); it maximises day-ahead profits, due to predicted market prices and time-band dependent DNO payments, subject to Eqs. (1)–(6).

$$max \sum_{nt} \left(\hat{p}^{DA}_{t} + \sum_{r} \mu_{rn} p^{DNO}_{rt} \right) \hat{P}^{exp}_{nt} \tag{7}$$

2.4. Real-time optimisation model

For the real-time optimisation, the MPC algorithm proposed in [28] is adopted and developed here; it works by implementing the following algorithm.

Algorithm 1: Real time optimisation

Solve DA model for all $t \in T$;
while $t \in T$ **do**
  Obtain solar output at current time period S_{nt} ;
  Forecast real-time settlement price $\hat{p}^{BM}_{t}$ at current time t, and future solar generation and price: $\hat{S}_{nt}$, $\hat{p}^{BM}_{t'}$ at time $t' \in T''$ where $T'' = \{t+1, \ldots, t+24\}$;
  Solve real time optimisation model:

$$\begin{aligned} max \sum_{n} \Bigg[& \left(\hat{p}^{BM}_{t} + \sum_{r} \mu_{rn} p^{DNO}_{rt} \right) (P^{exp}_{nt} - \hat{P}^{exp}_{nt}) \\ & + \sum_{t'=t+1}^{t+24} \left((\hat{p}^{BM}_{t'} + \sum_{r} \mu_{rn} p^{DNO}_{rt'})(P^{exp}_{nt'} - \hat{P}^{exp}_{nt'}) \right) \Bigg] \end{aligned} \tag{8}$$

  subject to equations (1) - (4) for $T' = \{t, \ldots, t+24\}$, equations (5) - (6) for $T'' = \{t+1, \ldots, t+24\}$, and:

$$P^{c}_{nt} \le S_{nt} \qquad \forall\, n, t \tag{9}$$

$$P^{exp}_{nt} = S_{nt} - P^{c}_{nt} + P^{d}_{nt} \qquad \forall\, n, t \tag{10}$$

  $t = t + 1$
end

Optimisations are carried out over 1 year from November 2016 to November 2017, corresponding to the solar data. Day-ahead and balancing market price data corresponding to this (November 2016 to November 2017) is used, since it is more realistic to use price data corresponding to the same time periods as the solar generation data. This is because factors affecting solar output, such as weather, will also affect market prices (via change in electricity demand and national renewable generation) and this needs to be taken into account.

The DNO payment data is taken from the most recent reports (2020–2021). We use more recent data for DNO payments, since these payments are decided upon before the start of each year and do not vary with factors such as solar output. Therefore, more recent data is preferred to capture more recent trends in use-of-system charges. On the other hand market prices, such as day-ahead and balancing market prices, may vary as a function of solar generation/weather; hence, day-ahead and balancing market prices need to correspond to solar generation data. The resolution of this model is hourly, since both day-ahead market prices and solar generation data have hourly resolution. Balancing market prices are half-hourly, therefore every other price, corresponding to half past the hour, was omitted. Most DNO time bands start and end on the hour; any other time band commencements not on the hour were rounded to the nearest hour.

In the optimisation models for both day-ahead and real-time markets, we assume that future prices and solar generation are unknown and we lack perfect knowledge of the future, which reflects the real-world operation of an ES optimiser. We also assume that the ES trading has no impact on prices and is considered a price-taker rather than a price-maker, which is valid when traded volumes are small relative to the total market. Previous research has shown that when price forecasting is imperfect, there is no significant difference in modelling storage as a price-maker or price-taker for storage capacities up to 500 MW in both day-ahead and real-time markets [61]. For the sake of simplicity the ES is modelled as a price-taker.

2.5. NPV calculations

The economic viability of installing ES in each location is also explored through calculations of its Net Present Value (NPV). This is of interest when (a) deciding whether the install ES with a pre-existing solar farm, or (b) deciding whether or not to include ES in plans for an upcoming solar farm. In [62] they present a report summarising a cost analysis of ES technologies based upon 2020 data, along with estimates for 2030. These were projected from the 2020 values by considering each technology's current state of development and using low, medium and high learning rates. Data was obtained from an extensive study of the literature, conversations with vendors, and responses to questionnaires.

The installation and maintenance costs associated with lithium iron phosphate (LFP) and lithium nickel manganese cobalt oxide (NMC) batteries is presented in Table 1. This is shown for 2020, with estimated values for 2030 in brackets. It can be seen that the prices of these batteries are incredibly similar; for the purposes of this work LFP batteries will be considered, since they perform the same or better than NMC on all cost metrics except for C^{BOS}. The typical lifetimes of these batteries are given in Table 1; they can also be calculated as the amount of time before capacity degrades to 80% of its initial value. The installation cost associated with ES, n, is shown in Eq. (11), and the yearly maintenance costs for year, y, in (12).

$$C_n^i = (C^{SB} + C^{BOS} + C^{SI} + C^{PD} + C^{CC})\bar{X}_n + (C^{PE} + C^{COMS} + C^{GI})\bar{P}_n \qquad \forall\, n \tag{11}$$

$$C_{ny}^m = C_y^{OMV}\bar{X}_n + C^{OMF}\bar{P}_n \qquad \forall\, n \tag{12}$$

The NPV of an ES project can be calculated using the following equation:

$$NPV_n = -C_n^i + \sum_{y=1}^{Y}\frac{(I_{ny} - C_{ny}^m)}{(1+r)^y} \qquad \forall\, n \tag{13}$$

Table 1
Costs associated with installation and maintenance of lithium iron phosphate (LFP) and lithium nickel manganese cobalt oxide (NMC) batteries, and their lifetime, in 2020 and estimates for 2030 in brackets [62]. A conversion of \$1 = £0.78 is used to convert these to pounds.

	LFP	NMC
Storage block (\$/kWh)	182 (109)	194 (116)
Balance of system (\$/kWh)	42 (30)	37 (26)
Power equipment (\$/kW)	85 (73)	85 (73)
Controls and communication (\$/kW)	40 (28)	40 (28)
System integration (\$/kWh)	50 (36)	51 (42)
Construction and commissioning (\$/kWh)	61 (50)	63 (51)
Project development (\$/kWh)	73 (60)	75 (62)
Grid integration (\$/kW)	31 (25)	31 (25)
Operations & maintenance fixed (\$/kW-yr)	4.40 (3.61)	4.51 (3.70)
Operations & maintenance variable (\$/kWh)	0.5125	0.5125
Lifetime	10	10

where r represents the discount rate and Y the end of project lifetime in years. The cash flow is equal to yearly ES income minus operations and maintenance costs, where yearly income is shown in Eq. (14) and is comprised of income from (1) the day-ahead market, (2) DNO payments and (3) the balancing market (this may be negative). In the final year the ES's residual value is also included as income; this is shown in Eq. (15).

$$I_{ny} = I_{ny}^{DA} + I_{ny}^{DNO} + I_{ny}^{BM} \qquad \forall\, n \tag{14}$$

$$I_{nY} = I_{nY}^{DA} + I_{nY}^{DNO} + I_{nY}^{BM} + R_n \qquad \forall\, n \tag{15}$$

The residual value is calculated using the declining balance method of depreciation, as described in [63]. It can be calculated using Eq. (16), where a is acceleration of depreciation and L is useful battery lifetime. Here, double depreciation, $a = 2$, is used since it is assumed battery value degrades quickly. The useful lifetime is calculated as: $L = Y + Y^{2ndlife}$. In other words, the lifetime of the project considered here (shown in Table 1) plus the second life lifetime. In [64] they assess the 2nd-lifetime of nickel metal hydride (NiMH) and lithium-ion batteries used for different purposes; an average value of 7 years can be calculated from this and will be used here.

$$R_n = C_n^i(1 - \frac{a}{L})^Y \qquad \forall\, n \tag{16}$$

3. Results and discussion

In this section we firstly explore the effects of location on the economics of a solar site, under the assumption that the solar generation is the same in all locations. This allows us to directly compare the effect of locational prices on economics. Then we remove this assumption and also examine the region differences due to weather. We then examine the economics required for a profitable co-located site, the effects of economies of scale and the minimum installation costs for profitable economics. Finally we discuss implications and limitations of this work.

3.1. Locational effects

For the initial simulations each solar site was co-located with ES with parameter values: $P_n = 0.4$ MW, $X_n = 0.2$ MWh, $\underline{X}_n = 0.04$ MWh, $\eta_n^d = \eta_n^c = 0.9$. Fig. 4 shows the results of when one arbitrarily chosen solar site was replicated in each of the DNO regions. In other words, each region contained one site with the same predicted/actual solar generation profile. The purpose of doing this is to compare directly the change in income due to different DNO payments. The mean and standard deviation of income through the different revenue streams: day-ahead market (DA), balancing market (BM) and DNO payments, is also shown in Fig. 5 for PV only and PV with ES.

Several things can be inferred from these results; firstly, the regional variation in income for PV only is very small (~£250), and the bulk

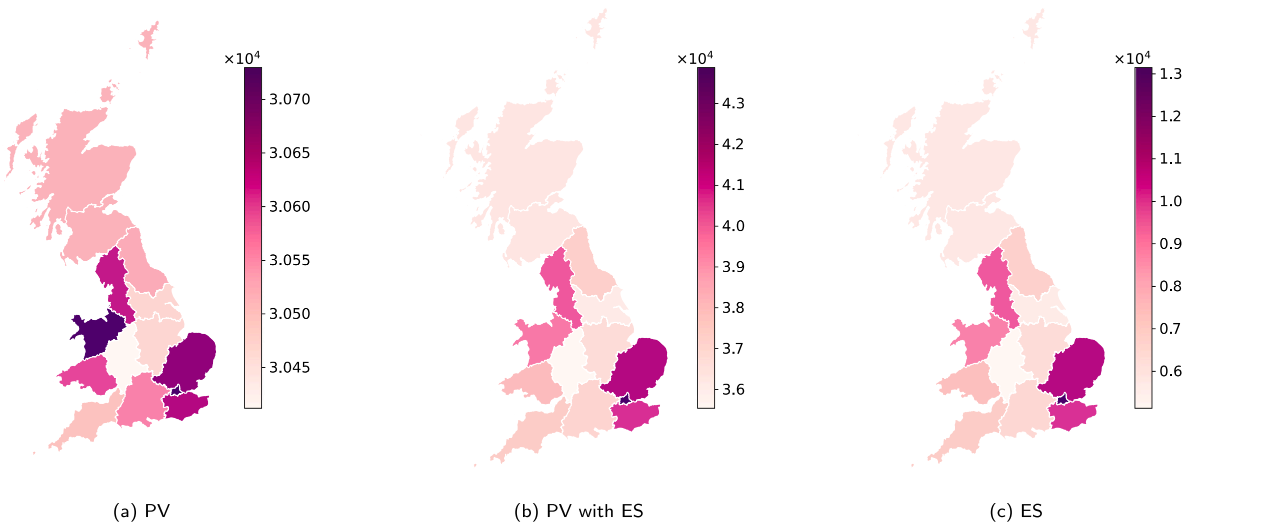


Fig. 4. Total yearly income (£) for one repeated solar profile in each region for PV only, PV with ES and improvement in income due to ES.

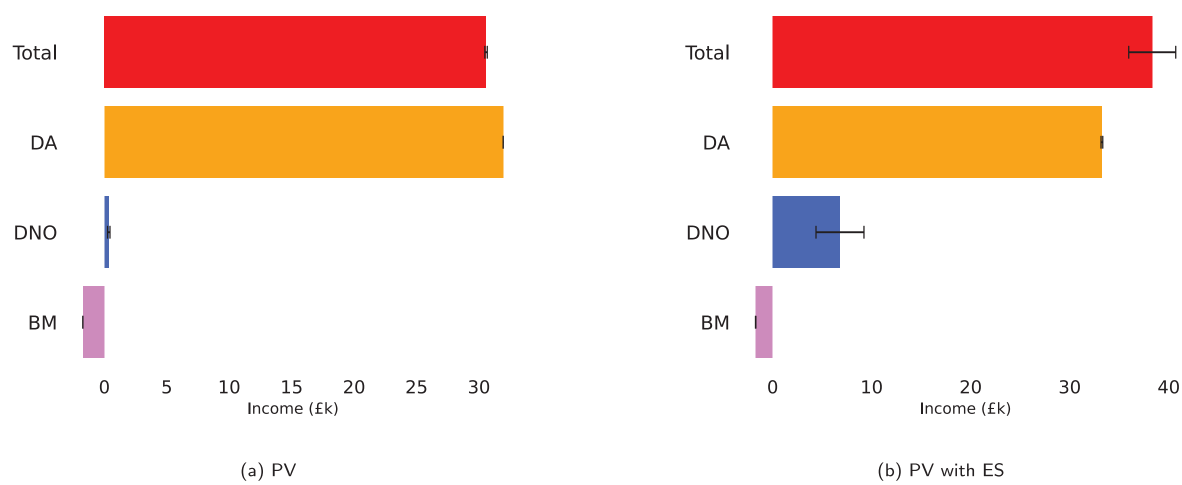


Fig. 5. Income breakdown for PV (left) and PV with ES (left) in day-ahead (DA) and balancing (BM) markets, due to DNO payments and total.

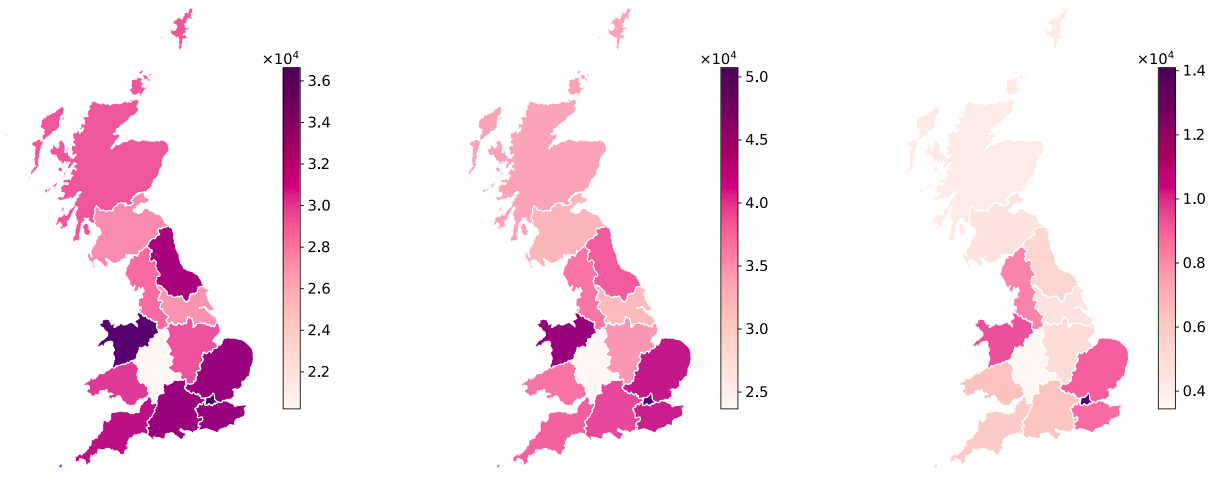
of the income comes from the DA market with very little DNO contribution. However, when storage is included a much larger variation in regional income is observed (∼£7000). Additionally, the inclusion of ES improves total income significantly; this is seen in all three revenue streams but in particular due to DNO payments. The consequences of this are that when considering locational options for PV only, regional income differences are not important. However, when looking to either install ES with existing PV or construct a new PV farm with ES, these regional differences will have a great impact on the site's economics (under current market conditions).

All 150 sites were used for the next simulation. Each one was located and its associated DNO identified, then they were all optimised using their unique solar profiles. The results of this therefore combine the regional DNO effects, previously discussed, with regional differences due to weather which affect the solar output. In Fig. 6 the average yearly income per site in each of the different DNO regions is presented. It can be seen that there is greater variation in PV income now that different solar profiles in each region have been used. As expected, the general trend is that PV in the southernmost regions generate high incomes due to improved solar irradiance. The outlier is the Western Power Distribution Midlands DNO region, which generates the least income. It can be seen in Fig. 3 that this region receives the lowest DNO payments. Additionally, the solar generation of sites within this region may compound this effect; for example, previous work suggests that inland solar sites may make greater financial losses in the balancing market [50]. The ES income follows the same trends as seen in Fig. 4, confirming that when deciding whether to include storage the DNO payments are the most important factor, rather than the output of the solar itself.

3.2. Economic viability

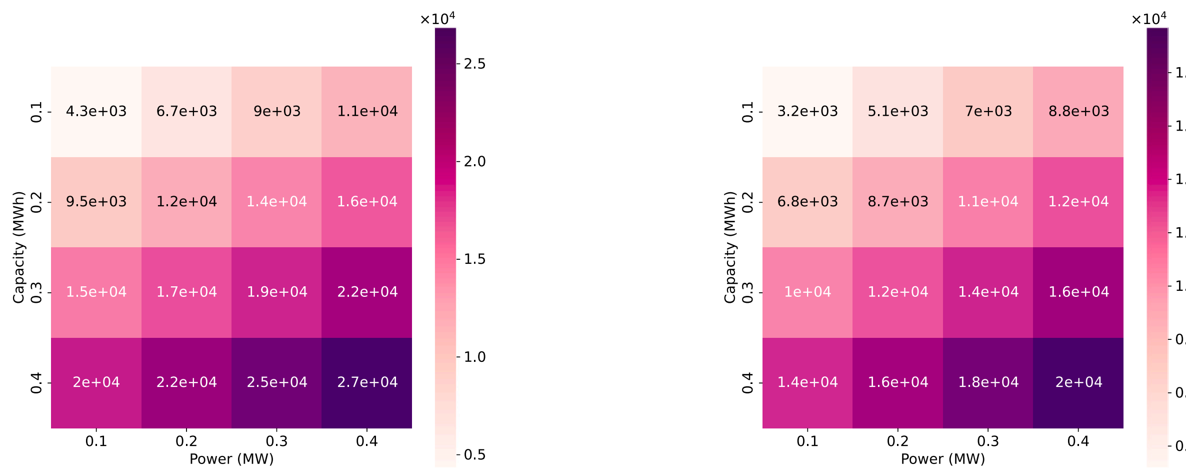
Fig. 7 shows the yearly ES income required (each year over its lifetime) to make NPV zero; this is done for LFP batteries using 2020 and 2030 cost values. A conversion rate of 0.78 pounds to one dollar has been used. In the previous section, ES incomes for a 0.2 MWh/0.4 MW battery were in the range £0.4–1.4×10^4; an LFP battery of this size needs to have an income of £1.7×10^4 or 1.4×10^4, using 2020 and 2030 prices respectively, in order to have a zero NPV. This is therefore are not profitable under current (2020) market conditions without additional incentives. However, it appears that smaller sized batteries could be profitable, hence, simulations will be done for 0.1 MWh/0.1 MW, 0.1 MWh/0.2 MW and 0.2 MWh/0.1 MW ES.

In Fig. 8 the average NPV for ES installed with solar in each region is shown. This is done using 2020 LFP battery costs and for different sized ES. It can be seen that ES is profitable in London, however, as this is a highly urban area it is unlikely for a solar farm to be installed here. For regions in south-east England and north Wales ES becomes



(a) PV (b) PV with ES (c) ES

Fig. 6. Average total yearly income (£) across each region for PV only, PV with ES and improvement in income due to ES.



(a) 2020 (b) 2030

Fig. 7. Yearly ES income (£) required to make NPV zero for different sized Lithium-ion batteries.

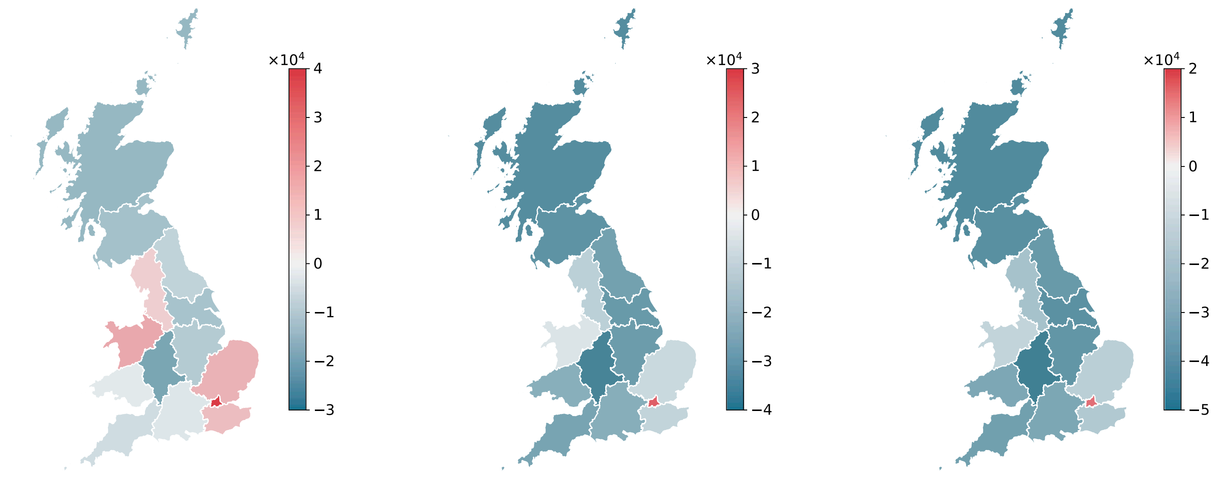
profitable when it is smaller e.g. 0.1 MWh/0.1 MW, although north Wales is also impractical due to its mountains. In other regions and for larger storage it is not profitable to co-locate ES with a solar farm.

Fig. 9 compares the average NPV values (for 0.1 MWh/0.1 MW) against the number of existing solar sites in each region as of June 2020; this data is obtained from the UK's Renewable Energy Planning Database [65]. We see that in the regions where ES is profitable there are relatively few solar farms - 25% of the total. In regions with the most solar farms, e.g. the South West, it is not profitable to add ES. One possible reason for this may be that due to the high capacity of solar generation in these regions there is less need for ES, and hence there is less need for advantageous DNO payments. Conversely, for regions where large scale solar is impractical due to population density (London) and mountains (North Wales), ES is more highly valued. This may be because their distribution grids have greater need for the support that energy storage can offer, for instance dispatchable generation and balancing services.

3.3. Economies of scale

The results presented thus far have modelled small-scale storage, $10^{-1} - 10^{0}$ MW. This is small relative to grid storage; according to the most recent Renewable Planning Database (April 2022), currently operational battery storage in the UK ranges from 0.1–50 MW, with larger projects submitted for planning permission [49]. Additionally, there is 2828 MW of pumped hydro storage in the UK. The largest of these, Dinorwig (1728 MW), provides fast acting response to balance the grid [66]. In comparison with these storage projects, the batteries modelled here are small. However, we are more concerned with performing a cost–benefit analysis from the point of view of a distribution-connected solar farm owner, than a transmission scale investor.

It is worth considering how the economics of adding battery storage to a solar farm varies as its scale increases. In particular, it is interesting to analyse whether it would benefit from economies of scale. In Fig. 10 the relative CAPEX (%) per MWh storage, compared against 1 MWh, is shown for different duration LFP batteries as duration increases to 10 and 100 MWh. It can be seen that increasing the size of the battery decreases the unit cost, particularly for lower duration/higher power batteries. This is since costs that scale with kW, shown in Table 1, such as controls and communication, and grid integration decrease relative to size [62]. It is likely that NPV is overestimated for the batteries in the previous section due to a decrease in size leading to



(a) 0.1 MWh/0.1 MW (b) 0.1 MWh/0.2 MW (c) 0.2 MWh/0.1 MW

Fig. 8. Average NPV across each region using 2020 lithium ion battery costs for different sized ES.

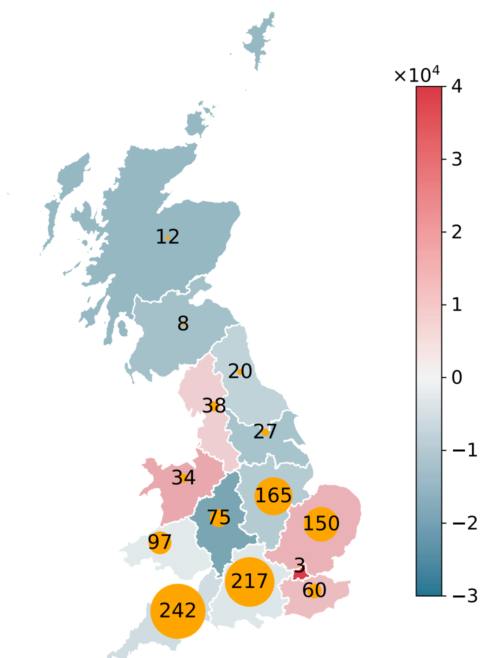


Fig. 9. Number of pre-existing solar sites in each DNO region as of June 2020. Plotted on 0.1 MWh/0.1 MW lithium ion battery average NPV (£).

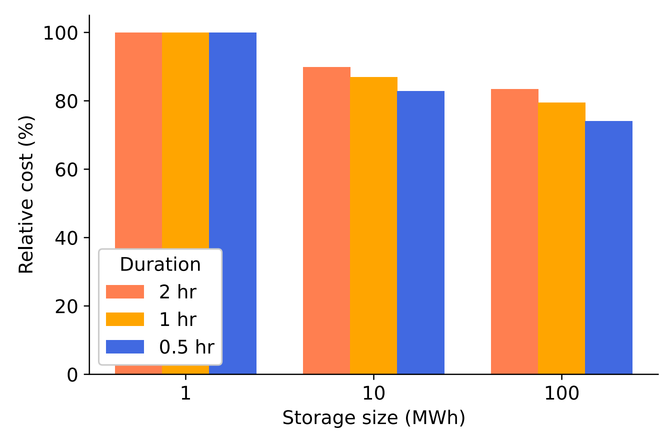


Fig. 10. Relative CAPEX (%) per MWh storage compared against 1 MWh, for different duration LFP batteries, as scale increases from 1 MWh to 10 and 100 MWh [62].

Table 2
Mean NPV and standard deviation for different solar and storage of different scale factors.

Max solar output, battery power/capacity	Mean NPV (£)	Std NPV (£)
1 MW, 0.4 MW/0.2 MWh	-6.02×10^4	1.35×10^4
50 MW, 20 MW/10 MWh	-2.38×10^6	6.68×10^5

an increase in relative costs. Hence, causing these batteries to also be an uneconomical investment for a solar farm participating in day-ahead and balancing markets.

To examine the effects of economies of scale, the simulations in Section 3.1 were repeated with solar and storage scaled by a factor of 50. The maximum output of the solar farms is 50 MW (representative of the maximum sized operating solar farms in the UK [49]) and the storage has maximum power 20 MW and capacity 10 MWh. The results of this are presented in Fig. 10 and Table 3. In Fig. 11 it can be seen that the scaled-up ES income follows the same geographic trends observed in Section 3.1. This is unsurprising as the optimised scheduling of the storage unchanged, the only difference is the magnitude of energy quantities exported. Table 2 compares the mean NPV and its standard deviation for the small-scale storage and the scaled-up storage. This calculation factors in the ES CAPEX, that is relatively reduced for the scaled-up battery. For both cases mean NPV is negative. However, it can be observed that the scaled-up battery benefits from economies of scale; if there were no economies of scale, it would be expected that mean NPV would be 50 times that of the small scale storage $\approx -3\times10^6$. Despite the slight improvement, it is still not economical for a solar farm owner to add ES for arbitrage.

3.4. Minimum installation cost

The cost of lithium-ion batteries fluctuates due to various factors, including raw material prices, manufacturing scale, technological advancements, and government policies and incentives. This means that the prices used here might not reflect current market values. Therefore, it is instructive to flip the research question and ask: at what cost does it become profitable to add ES to a solar PV site?

We calculate the minimum installation cost at which it becomes profitable to add ES by rearranging Eq. (13) with NPV equal to zero.

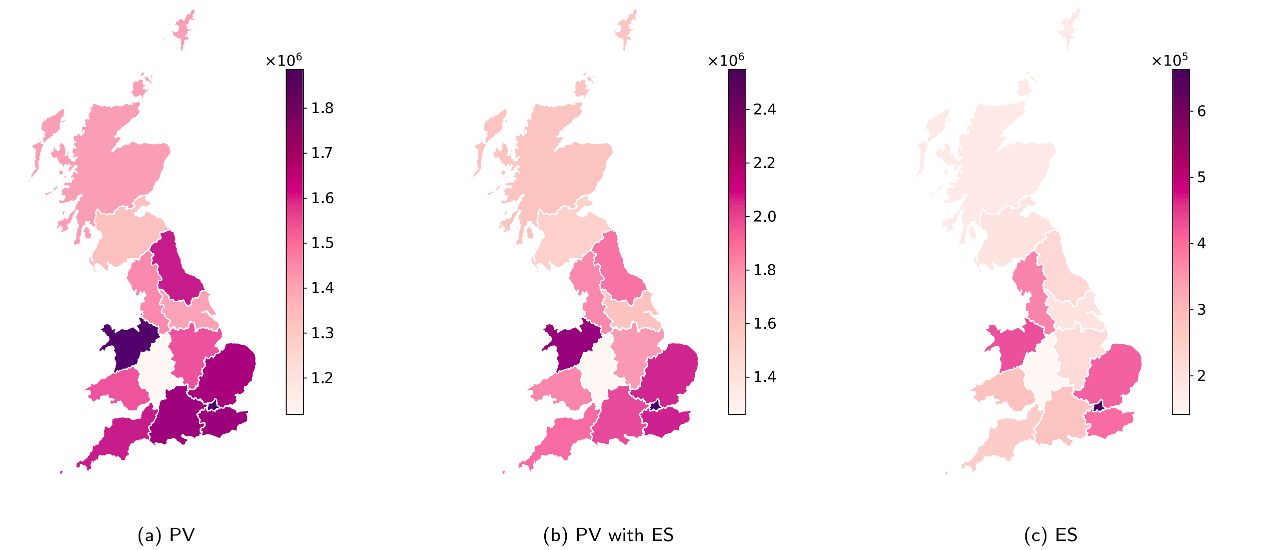


Fig. 11. Average total yearly income (£) across each region for PV only, PV with ES and improvement in income due to ES. Scaled up by factor 50, in comparison with Fig. 6.

Table 3
Mean minimum installation costs (£/kWh) required to make NPV zero.

Power (kW)	Capacity (kWh)	Duration (h)	Mean minimum installation costs (£/kWh)
100	50	0.5	394
100	100	1	410
100	200	2	258

The results are shown in Table 3, for different battery durations. It should be noted that these values include all aspects of installation costs, including system integration, project planning, power equipment etc. as well as the material cost of the battery.

Adding a 1-h duration (100 kW/100 kWh) battery to a solar PV site becomes profitable when the installation cost reaches or falls below £410/kWh. However, as the duration increases to 2-h, a lower installation cost of £258/kWh is required to generate a profit. This is because while the energy capacity of a 2-h battery doubles that of a 1-h battery, the profits are less than double, making a cheaper cost necessary for a profitable installation. The minimum installation cost for a 0.5-h duration battery is similar to that of a 1-h battery, at £394/kWh. Although material costs are lower for a 0.5-h battery, the profits are also lower.

In Fig. 12 we show how the mean minimum installation costs vary for the different DNO regions. As seen previously, greater income can be achieved in London, the south-east and north Wales. In these regions, the minimum installation costs required for ES to become profitable are much higher. In London, the mean cost is £839/kWh. Adding ES in these regions is still beneficial when material and manufacturing costs are high. In the West Midlands, installation costs must fall below £100/kWh to be profitable to add ES to a PV site.

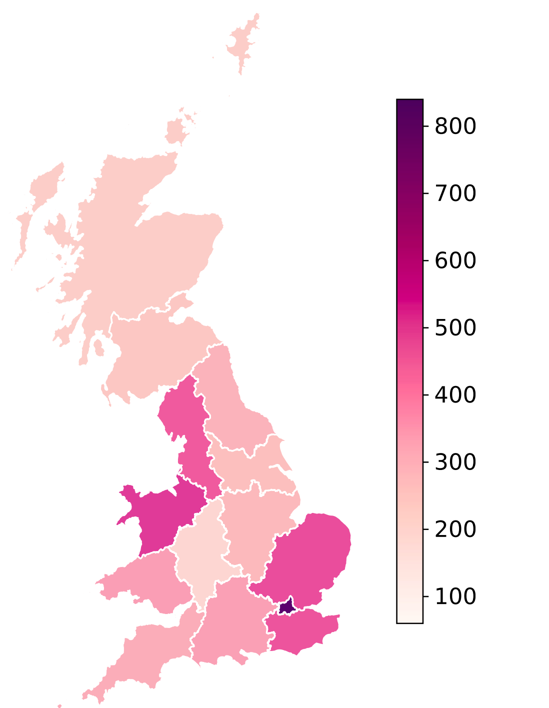


Fig. 12. Mean minimum installation cost (£/kWh) in each DNO region for a 1-h (100 kWh/100 kW) battery.

3.5. Discussion

The findings suggest that under the studied market conditions it is uneconomical to add ES to most existing solar farms in the UK for arbitrage. Consequently the unique benefits of co-locating ES with solar, such as capturing clipped power and reducing curtailment, may not be realised. To encourage increased co-location, there should be greater cost benefits for the solar farm owner. These might include greater differential Use-of-System pricing to favour non-intermittent generation over intermittent generation. Specifically, ES investments could be encouraged by increasing Use-of-System payments during red time bands, when demand is at its peak.

Interestingly, it was observed that due to the regional nature of GB's DNO Use-of-System charges, it is more economical to incorporate ES in some regions than others. However, the regions where adding ES is economically favourable do not correspond to those with the most existing solar sites, nor those with the greatest solar irradiance. This is an unusual observation, and reflects the fact that in GB different regional operators may set their own pricing. Similar analysis may be performed in regions outside of GB, where differences in regional market structures lead to differing locational economics. In [67] the authors explore the economics of hybrid renewable-storage systems participating in 7 different US wholesale markets; these include CAISO (California Independent System Operator), ERCOT (Electric Reliability

Council of Texas) and NYISO (New York Independent System Operator), amongst others. The net value is found to differ regionally, and also as a function of battery duration and capacity, and year. A review of Distribution System Operators (DSOs) in Europe shows that some countries have a larger number of DSOs (Germany, Spain, Poland), whereas other countries have 1 (Croatia, Greece, Ireland) [68]. Examining these further is outside of the scope of this work, but it would be interesting to explore whether similar regional effects are observed within these countries.

Limitations of this study are that it only considers battery revenues from merchant markets, namely the day-ahead market and Balancing Mechanism. In reality, a battery might also generate revenue by participating in ancillary service market. For example, it could participate in frequency response and reserve markets during times when it is not trading in merchant markets. Additionally, this model does not consider battery degradation. Heavily battery cycling (charging and discharging) leads to accelerated degradation and reduces its lifetime. This can be expensive, due to the cost of replacing the battery. Often batteries have warranties in place to limit cycling. It would be interesting future work to include revenues from ancillary service markets and to also include some degradation constraints in the optimisation model, to examine how these factors affect the economics.

Finally, it is acknowledged that changes will shortly be taking place in the way distribution grids function. DNOs will be transitioning towards DSOs (Distribution System Operators); this reflects the transition towards more decentralised electricity grids, with local generation and changes in usage patterns. The DSOs will have more control over the local grids and use smart technologies for the management of the network [69]. It is unclear what the consequences will be for the Use-of-System charges, however, there is emphasis on supporting low carbon technologies, such as ES, in local electricity grids [70]. Hence, it is expected that the upcoming changes will improve the profitability of ES. Specifically, for co-location of ES with solar to become more economically advantageous for solar farmers, it is recommended to increase the differential between non-intermittent generation and intermittent generation payments, and increase non-intermittent payments during red time bands.

4. Conclusion

In this work we have presented a mixed integer linear programming (MILP) optimisation model to explore the economic impact of location on a solar farm co-located with energy storage (ES). The model combines economics and location (usually considered separately). It is easy to replicate and apply to different case studies, making it a useful tool for decision-making for battery storage projects. This work is of interest to distribution-connected solar owners and organisations considering investing in low-carbon energy assets. We determine how the maximum achievable profits of a solar farm with and without ES in different regions around Great Britain (GB) vary, and in which regions ES adds more value. Our results show that solar farms without ES are more profitable in regions with higher solar irradiance and profits are relatively unaffected by differences in local grid charges. On the other hand for solar farms with ES the regional profits are more varied and strongly affected by local charges.

We find that ES adds greater value in regions where there are fewer existing solar farms. These are often regions where it is geographically impractical to build solar farms. Additionally net present value (NPV) calculations show that it is only profitable to add small ES (0.1 MWh/0.1 MW) to a solar farm. This is only profitable in select regions containing 25% of GB's total existing solar farms. Hence for the majority of these it is not economical to add ES. These findings are important because recent studies suggest that we should be adding more ES to solar; since it can reduce clipping and curtailment, and optimises its usage. Our findings suggest that solar owners could lose out on these benefits unless distribution network and market pricing is changed to favour ES, specifically by increasing the differential between non-intermittent generation and intermittent generation payments.

Future work may look at studying the degradation of ES due to its co-location with solar. It may be interesting to examine how including degradation in the optimisation function affects its profits and lifetime, and if this in turn affects its optimum location. Future work may also aim to predict future distribution grid charges, using historic trends, and repeating this analysis as and when any changes are made. Modelling the future volatility of day-ahead and balancing market prices is also an area of development which will influence the value of ES. Finally, the model outlined here may be applied to any other country, or countries, where there is variation in regional distribution grids. It is hoped that work will bolster the deployment of ES, particularly co-located with solar, to improve power grids and enable the decarbonisation of electricity systems.

CRediT authorship contribution statement

F.A.V. Biggins: Conceptualization, Methodology, Software, Visualization, Writing – original draft. **D. Travers:** Methodology, Writing – review & editing. **J.O. Ejeh:** Software, Writing – review & editing. **R. Lee:** Writing – review & editing. **A. Buckley:** Writing – review & editing. **S. Brown:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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