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Using electricity storage to reduce greenhouse gas emissions

Andrew J. Pimm [a,*], Jan Palczewski [b], Edward R. Barbour [c], Tim T. Cockerill [a,d]

[a] School of Chemical and Process Engineering, University of Leeds, Leeds LS2 9JT, UK
[b] School of Mathematics, University of Leeds, Leeds LS2 9JT, UK
[c] School of Mechanical, Electrical and Manufacturing Engineering, Loughborough University, Loughborough LE11 3TU, UK
[d] School of Mechanical Engineering, University of Leeds, Leeds LS2 9JT, UK

HIGHLIGHTS

- The regional impacts of storage operation on CO_2 emissions are studied.
- A new method of determining regional emissions factors was developed.
- Emissions factors found using linear regression and a power flow model.
- Large differences in emissions across storage operating scenarios and regions.
- Differences in Great Britain can be equivalent to fitting coal power with CCS.

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ABSTRACT

While energy storage is key to increasing the penetration of variable renewables, the near-term effects of storage on greenhouse gas emissions are uncertain. Several studies have shown that storage operation can increase emissions even if the storage has 100% turnaround efficiency. Furthermore, previous studies have relied on national-level data and given very little attention to the impacts of storage on emissions at local scales. This is an important omission, as carbon intensities can vary very significantly at sub-national scales. We introduce a novel approach to calculating regional marginal emissions factors, based on a validated power system model and regression analysis. The techniques are used to investigate the impacts of storage operation on CO_2 emissions in Great Britain in 2019, under a range of operating scenarios. It is found that there are significant regional differences in storage emissions factors, with storage tending to increase emissions when used for wind balancing in areas with little wind curtailment. In contrast, the greatest emissions reductions are achieved when charging storage with otherwise-curtailed renewables and discharging to reduce peak demands in areas consuming high volumes of fossil fuel power. Over all regions and operating modes studied, the difference between the highest reduction in emissions and the highest increase in emissions is considerable, at 741 gCO_2 per kWh discharged. We conclude that power system regulators should pay increased attention to the impact of storage operation on system CO_2 emissions.

1. Introduction

Electricity storage is key to enabling the grid integration of non-dispatchable low carbon electricity generation at large scales. Storage costs have dropped considerably over recent years through improvements in technology and manufacturing, and the scale of deployment is now beginning to increase. This is particularly noticeable for electrochemical storage, with batteries being mass produced for electric vehicles and consumer electronics [1]. Further cost reductions are expected [2], meaning that the penetration of storage in electricity systems is likely to increase significantly more over the medium term. This will enable further expansion of non-dispatchable low carbon generation, which in turn will contribute to decarbonising electricity systems.

The short-term impact of increased storage penetration on electricity-derived carbon dioxide emissions is much less clear. It is widely understood that inefficiencies associated with storage naturally increase the carbon intensity of all electricity passing through [3]. Previous investigations have found that using storage to arbitrage on electricity prices, or shift load from times of high demand to times of low

* Corresponding author.
E-mail address: a.j.pimm@leeds.ac.uk (A.J. Pimm).

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Nomenclature

a	Regression Coefficients
C	Consumption-based CO_2 Emissions
D_n	National Electricity Demand
D_{net}	National Electricity Demand Net of Wind and Solar Generation
D_r	Regional Electricity Demand
G_{PV}	Generation from Solar PV
G_w	Generation from Wind
i	Grid Supply Point Group ID
m	Marginal Emissions Factor
AEF	Average Emissions Factor
CCS	Carbon Capture and Storage
ESO	Electricity System Operator
GSP	Grid Supply Point
MEF	Marginal Emissions Factor

demand, can lead to a significant rise in emissions *even if the storage has a turnaround efficiency of 100%* [4–8]. The impact is dependent upon the marginal emissions factors (MEFs) when the storage is charged and discharged, with MEFs being the effect on emissions of a change to system load [9].

If the output from a high carbon source (such as coal or gas) is increased to charge storage, and the output from a lower carbon source is reduced as a consequence of the storage discharging, then net emissions are increased as a result. As the converse is equally true, there is evidently an urgent need to understand how the operation of storage systems will impact on net emissions from an electricity system, which is our purpose in this paper.

MEFs depend upon the marginal generator(s) in a given time interval, and can be contrasted with average emissions factors (AEFs, or “carbon intensity” [10]), which depend upon the whole mix of generation in the same time interval [11]. MEFs are typically used to understand the impacts of an intervention in the energy system (such as operating storage) on CO_2 emissions, because using AEFs would imply that all generators vary their output in response to any changes in load. AEFs are generally used for carbon accounting [12] as it is difficult to calculate MEFs with high levels of accuracy, particularly in electricity systems like that of Great Britain (GB) that do not use centralised ‘optimal dispatch’. However, multiple previous investigations have found that using AEFs can considerably miscalculate the emissions associated with an intervention [13–16].

The literature sets out two classes of approach to determining short-run MEFs, one drawing on economic dispatch models, and the other synthesising statistical models based on empirical data. Most dispatch models assume a merit order-based approach to generating plant dispatch, with individual units dispatched in order of marginal cost, such that the last generator required sets the marginal emissions rate for the whole system [15]. Dispatch models have been used to derive MEFs in the US [17–20] and Europe [13,21,22], frequently using generator utilisation (i.e. capacity factors) as a proxy for variable operating cost and hence position in the merit order. A small number of studies have explored emissions-based merit orders [23]. Statistical models typically employ linear regressions of historical data to calculate MEFs. This approach was used by Hawkes on half-hourly system data from Great Britain over the period 2002–2009 [9] (building on foundations laid by others [24,25]) and by Thomson *et al* to understand the avoided emissions from use of wind power from 2009 to 2014 [26]. Linear regression has also been used to determine MEFs for Ireland [8], the US [6,7,15,16,27], and Portugal [28].

In 2017, McKenna *et al* [8] investigated the short-run impact of electricity storage on CO_2 emissions via a case study of Ireland. Data on the observed dispatch of each large generator over the period 2008–2012 were used to determine marginal generator responses for each generator type using a linear regression approach. It was found that CO_2 emissions were increased in the short-term for all storage technologies when operated in load shifting (i.e. peak shaving / trough filling) and wind balancing modes. The results highlight a key tension between economic and environmental objectives, however the approach is focused on a single relatively isolated region and cannot be applied with confidence to study highly interconnected regions unless it is certain that imports from other regions are insignificant.

In 2019, Sun *et al* [23] introduced a method of arbitraging on emissions factors to reduce the environmental impact of domestic PV-battery systems. This involved forecasting time series of MEFs in Great Britain out to 2050 using energy scenarios developed by the UK electricity system operator [29], and investigating the environmental benefits of arbitraging on CO_2 emissions. It was shown that emissions arbitrage could be used to achieve additional CO_2 savings that more than pay back the emissions associated with the battery’s manufacture.

Very few studies explicitly examine the extent to which MEFs vary within national transmission systems. A very limited number of studies note that geographical location can be important [6,7,15,30]. In 2015, Hittinger and Azevedo [6] calculated the impacts of storage operation on CO_2 emissions in 20 US eGRID subregions, showing that emissions resulting from storage operation are nontrivial and vary significantly by location. This was backed up by more recent research by Li *et al* [31]. Crucially, however, the researchers in those studies used production intensities in each region to determine the regional impacts of storage operation rather than consumption intensities, which would more accurately reflect the way that carbon emissions are altered through changes to demand.

The importance of focusing on consumption rather than production was reinforced by Danish research in 2019, in which flow tracing was used to track electricity flows by country of origin and generation technology [30]. It was found that the differences between production and consumption CO_2 intensities are significant in countries that import power from countries with different generation mixes to their own. Austria, for example, has significant hydro power capacity, giving it a production intensity of only 136 gCO_2/kWh. However, it is heavily reliant on coal power imported from the Czech Republic and Poland, so its consumption intensity is 82% higher, at 248 gCO_2/kWh.

From our comprehensive review of the literature, it is clear that the relationship between the location of an electricity storage system and the CO_2 emissions arising from its operation is poorly understood. The work presented here seeks to address this gap in the knowledge base. It is the first research to fully consider how the operation of electricity storage impacts on net CO_2 emissions on a sub-national basis, and the first to resolve power flows when considering sub-national MEFs, hence more accurately determining the effects of changes to electricity demand on generation mixes and CO_2 emissions. Our aim is to identify how storage can be operated strategically to reduce net emissions, or at least minimise any increase due to the associated energy losses. The GB electricity system is used as a case study, but the techniques developed here could be applied to any country or region. We build on our earlier preliminary investigation [32] by: i) introducing a new approach to calculating regional MEFs which takes renewables generation into account; ii) evaluating the accuracy of the techniques used; and iii) comparing new storage operating scenarios.

Our analysis begins by examining the characteristics of CO_2 emissions from the GB electricity system at a national scale. Subsequently we demonstrate the importance of considering marginal emissions at a regional rather than national level. Finally, we focus on the implications of regional differences between MEFs and determine the impact of location on the effectiveness of storage for reducing greenhouse gas emissions. Our major contributions are thus:

- A detailed investigation into the regional variation in marginal emissions factors from grid electricity.
- Determination of the effects of electricity storage operation on CO_2 emissions.
- Drawing of firm conclusions regarding the strategic operation of storage.

To accomplish our objectives, we develop two statistical approaches to calculating regional MEFs and apply these techniques to Great Britain in three different storage operating scenarios. To the authors' knowledge, this is the first work to investigate emissions factors and the impacts of storage on a regional level while fully accounting for the source of electricity.

2. Evaluating emissions from the GB electricity system

To provide context, we begin our analysis by characterising emissions from the whole GB national electricity system, applying existing approaches from the literature to calculate marginal emissions factors (MEFs) and average emissions factors (AEFs, or "carbon intensity") with up-to-date data. Following this, Section 3 introduces the methods used to calculate emissions factors at local scales and assess the impact of storage operation on grid CO_2 emissions.

2.1. Determining national emissions factors

MEFs can be calculated using the linear regression approach introduced by Hawkes [9]. A scatter plot is created, of half-hourly changes in the carbon emissions from grid-connected generators (ΔC) against the corresponding changes in national electricity demand (ΔD_n), and a line-of-best fit is fitted to the data, of the form $\Delta C = m\Delta D_n$, with the gradient m being the MEF, typically expressed in gCO_2/kWh. Time series of electricity generation data for Great Britain, aggregated by fuel type, are provided by National Grid ESO, the GB electricity system operator, via BM reports [33], and data for the years 2017–2019 are used here, at half-hour resolution. The carbon intensity factors employed for each source of power are given in Table 1.

Table 1
Carbon intensity factors for each source.

Power Source	Carbon Intensity (gCO_2/kWh)
Biomass	120
Coal	937
Dutch Imports	474
French Imports	53
Gas (Combined Cycle)	394
Gas (Open Cycle)	651
Hydro	0
Irish Imports	458
Nuclear	0
Oil	935
Other	300
Pumped Storage	0
Solar	0
Wind	0

Source [34]

Here we adopt Hawkes' methodology to calculate national-level MEFs over a range of system net demands (i.e. demand net of solar and wind generation, $D_{net} = D_n - G_{PV} - G_W$). There is little correlation between total electricity demand and wind/solar output, and so the inclusion of wind and solar data in the regression would lower the quality of the fit; a similar approach has been used by others [8]. The generation data is binned according to system net demand, and then national-level MEFs are calculated for each bin using linear regression. A representative scatter plot for one bin is shown in Fig. 1. The outcome is shown in Fig. 2, with system net demand bin widths of 2.5 GW. 99% confidence intervals on the MEF values are also shown in Fig. 2, along with AEFS. The AEF in each bin is simply the total CO_2 emissions associated with the binned data divided by the total system net demand values for the binned data.

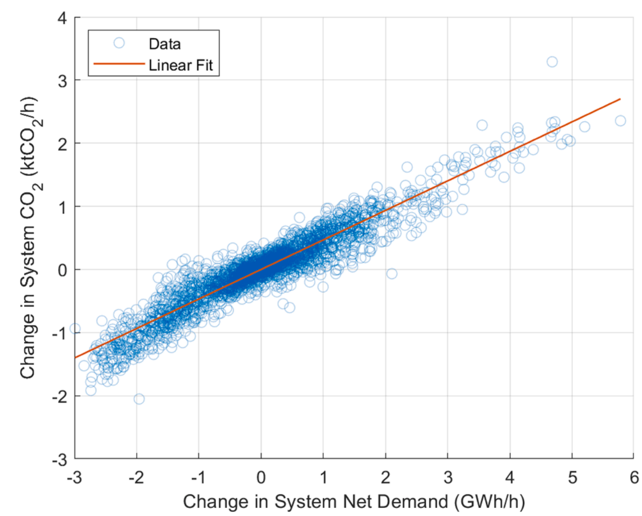

Fig. 1. Scatter plot used to calculate national-level MEF for a 2.5 GW wide bin centred on system net demand of 37.5 GW.

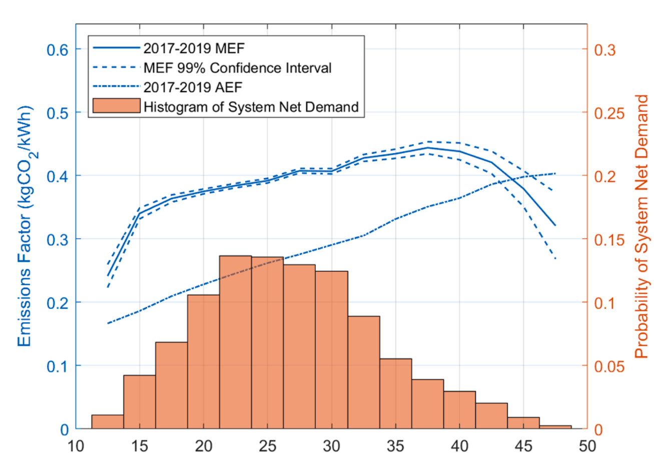

Fig. 2. Emissions factors over 2017–2019 binned by system net demand (blue curves), along with probability of system net demand (red bars).

2.2. Impacts of decarbonisation

The shape of the MEF profile in Fig. 2 can be compared with that developed by Hawkes using data for Great Britain over the period 2002–2009 [9]. Several features are of note. Firstly, MEFs averaged over the years 2017–2019 are lower than the minimum MEFs over the period 2002–2009, at all levels of system net demand. This is a result of the large-scale replacement of coal, open cycle gas, and oil generation with low carbon wind, solar, combined cycle gas, and biomass generation [35]. Secondly, the highest emissions factors now occur at much higher levels of system net demand, largely because gas power is now prioritised over coal power in the effective merit order of dispatch. The trend of coal shifting in the merit order was already observed by Hawkes over the period 2002–2009, and has subsequently continued in the GB electricity system [36].

The drop-off in MEF at very high levels (>40 GW) of system net demand is now a result of hydropower and pumped storage being dispatched at these levels, which we treat as having zero net emissions at the time of dispatch. The electricity provided by pumped storage may of course have come from carbon dioxide emitting sources, however our methodology attributes those emissions to the original generation of that electricity, rather than its release from the store.

2.3. Average vs marginal emissions factors

Comparing AEFS and MEFs, it can be seen that AEFs greatly underestimate the impact of a change in demand, except at times of very high demand when they provide a significant overestimate. This clearly demonstrates the necessity of employing MEFs, rather than AEFs, in determining the environmental impacts of an intervention to the electricity system, agreeing with Hawkes [9].

The shape of the MEF curve also illustrates the need to think carefully about the impact of storage operation strategies on net emissions. If a newly commissioned storage system is charged from the grid during periods of moderate net demand, say 25 GW, it will draw on higher carbon electricity than is available at the times of highest net demand. Thus, discharging that storage during peak periods, when there is likely to be the maximum benefit from financial arbitrage, will result in a net increase in overall emissions even if there are no losses. Assuming a round-trip storage efficiency of 75%, the MEF curve in Fig. 2 implies that grid-charged storage will increase net emissions if it is discharged at the times of highest net demand: even if the storage is charged at the time of the lowest MEF (0.24 $kgCO_2/kWh$), storage losses would mean that emissions released in charging the storage would exceed the emissions displaced when discharging at peak net demand (when the average MEF is 0.32 $kgCO_2/kWh$).

3. Data and methods

We now present the methods used to determine MEFs at a regional level and investigate the relationship between electricity storage operation and CO_2 emissions. Vectors and arrays are denoted in bold.

3.1. Assumptions

As our intention is to provide the first evaluation of materiality, we make simplifying assumptions. The most significant is that we assume charge/discharge operations have no direct impact on the system electricity generation mix. For the current low penetration levels of storage (other than pumped storage, which is included in our analysis of generation mix) this is a good approximation to reality. In the future, with the much greater storage penetration levels anticipated, charging and discharging operations may have a substantial impact on the generation mix. However, during the 10–20 year timescale over which it is expected that storage will be deployed at scale, there are also likely to be large changes in installed generating capacities.

This brings us to a second set of assumptions implicit in our analysis, specifically that (i) generation mixes remain statistically stable over time (in terms of the relationship between demand and the generation types used to meet that demand), and (ii) that grid carbon intensity is at least partially correlated with demand. As shown by the relatively tight confidence interval on MEFs against system net demand in Fig. 2, for the GB electricity system these assumptions appear valid at a national scale and over the time periods analysed in this paper. As will become evident later, they are only tenable in certain regions, and this constrains the scope of our regional analysis. Over the long term, of course, it is expected that generation mixes will increasingly incorporate more decarbonised sources, thereby greatly reducing temporal variations in the carbon intensity of electricity. While our methods will remain valid so long as there is still a relationship between demand and carbon intensity, clearly our numerical results will need to be re-evaluated in the context of future decarbonised electricity systems.

Finally, in this work we simplify the treatment of fossil generation by assuming a constant efficiency at all outputs, and hence use a single emissions factor for each generation technology, as given in Table 1. In reality, CO_2 emissions from fossil generation are increased by part-loading and plant start-ups, with recent research indicating that dynamic plant efficiency may reduce the calculated carbon savings from wind by 5–12% and from solar by 0–6% [37]. Fully accounting for dynamic plant efficiency in our research would require an understanding of how individual fossil generators respond to changes in system demand, and such detail is considered to be beyond the scope of this work.

3.2. Determining regional marginal emissions factors

To evaluate the impact on CO_2 emissions of a change in a particular region's electricity demand, it is important to approximate the region's consumption-based emissions, i.e. the emissions associated with its electricity consumption, accounting for electricity network connections and the distribution of generation and demand. For this reason, a power flow model is required to calculate flows in the electricity grid and determine the source of consumed electricity. This method has been used in Great Britain by Bruce and Ruff [34] on behalf of the electricity system operator (National Grid ESO), with the output publicly available via the ESO's Carbon Intensity website and API [38]. The API provides historical regional carbon intensity data at half hour resolution, as well as forecasts up to 48 h hence. It is built around a reduced network model of Great Britain, which is used to calculate the CO_2 transfers between importing and exporting regions, taking account of system losses and network constraints.

To convert regional consumption-based carbon intensities to regional carbon emissions, regional electricity demand data are required at the same temporal resolution. The product of the consumption-based carbon intensities in a given region (in gCO_2/kWh) and the electricity demands in that region (in kWh) then gives the region's consumption-based emissions. In Great Britain, "Grid Supply Points" (GSPs) form the interface between the high voltage transmission network and the lower voltage distribution network. GSPs are grouped geographically to split the distribution network into 14 distinct Distribution Zones, also known as GSP Group Regions (or alternatively as "DNO License Areas" or "Public Electricity Supplier regions"). Half-hourly electricity import/export data for the GSP Groups are made available by ELEXON in the CDCA-I029 report. To these data, we add regional solar PV generation as provided through the PV_Live API [39], as solar PV in Great Britain is connected at distribution level and is seen as a reduction in demand.

We use this data to determine MEFs using two separate approaches, henceforth known as *enhanced linear regression* and *simple linear regression*. These are outlined below.

3.2.1. Enhanced linear regression

In determining the marginal impact of a region's electricity demand on its consumption-based CO_2 emissions, our enhanced regression approach accounts for the region's demand and national demand, as well as the wind and PV generation. As such, we create a linear fit of the form

$$\Delta C_i = \left(a_{0,i} + a_{1,i} D_{r,i} + a_{2,i} D_n + a_{3,i} G_{PV} + a_{4,i} G_w\right) \Delta D_{r,i} \tag{1}$$

where ΔC_i is the change in regional consumption-based emissions in region i, $D_{r,i}$ is the regional demand, D_n is the national demand, G_{PV} is the national solar generation, G_w is the national wind generation, and $\Delta D_{r,i}$ is the change in regional demand. The vector of regression coefficients, $\boldsymbol{a_i}$, is determined through the least-squares solution to the system of equations

$$\boldsymbol{\Delta C_i} = \left[\, \boldsymbol{\Delta D_{r,i}} \quad \boldsymbol{D_{r,i}} \circ \boldsymbol{\Delta D_{r,i}} \quad \boldsymbol{D_n} \circ \boldsymbol{\Delta D_{r,i}} \quad \boldsymbol{G_{PV}} \circ \boldsymbol{\Delta D_{r,i}} \quad \boldsymbol{G_w} \circ \boldsymbol{\Delta D_{r,i}} \,\right] \boldsymbol{a_i} \tag{2}$$

where $\boldsymbol{\Delta C_i}$, $\boldsymbol{\Delta D_{r,i}}$, $\boldsymbol{D_{r,i}}$, $\boldsymbol{D_n}$, $\boldsymbol{G_{PV}}$, and $\boldsymbol{G_w}$ represent vectors of time series data. While solar generation data is available at regional level, national-level data is used in the regression as it was found that using regional-level solar data has little effect on the goodness of the fit.

A time series of marginal emissions factors in region i is thus given by

$$\boldsymbol{m_i} = a_{0,i} + a_{1,i} \boldsymbol{D_{r,i}} + a_{2,i} \boldsymbol{D_n} + a_{3,i} \boldsymbol{G_{PV}} + a_{4,i} \boldsymbol{G_w} \tag{3}$$

As explained above, the regional consumption-based carbon emissions $\boldsymbol{C_i}$ are determined for Great Britain by multiplying the CDCA-I029 regional electricity demand data by the regional carbon intensity data (from National Grid ESO's Carbon Intensity API).

Since the regional electricity demand data is currently only available to us up to 1st January 2020, and the carbon intensity data is only available from 14th May 2018, the investigations presented here are based on data covering the 2019 calendar year. The historical carbon intensity data is a new dataset, and this is one of the first studies to use it.

3.2.2. Simple linear regression

Our enhanced linear regression technique, as set out above, is compared with Hawkes's simpler linear regression method, wherein a simple linear relationship is developed between changes in regional electricity demand and changes in regional consumption-based emissions, of the form

$$\Delta C_i = m_i \Delta D_{r,i} \tag{4}$$

An example of this was shown in Fig. 1. Here MEF m_i is constant over time, unlike in the enhanced approach.

3.3. Accuracy of the methods

Using both the methods laid out, regional MEFs for the 14 electricity distribution zones of Great Britain have been determined, and the R^2 values for the fits are shown in Fig. 3. The resultant MEFs in selected regions are presented later in Section 4.1. Scatter plots for the regions providing the best and worst fits, Yorkshire and South Scotland respectively, are shown in Fig. 4. The source of electricity consumed in each region has also been calculated by multiplying the regional generation mix data made available through the Carbon Intensity API (percentage of fuel type consumed in each region at each half hour) by the half-hourly regional demand data. This is shown in Fig. 5.

It can be seen that the enhanced fits have slightly higher R^2 values than the simple fits in all regions, explaining more of the variance in the data. However, goodness of fit varies widely across the regions and in several regions R^2 values are low as 0.1 indicating that demand is not a useful predictor. From Fig. 5 it can be seen that the best fits are found in areas consuming high levels of gas, coal, and biomass generation. This is to be expected, with the high R^2 values corresponding to areas which have a consumption mix that is statistically stable over time and correlated with demand.

Conversely, the low R^2 values are associated with areas that exhibit large temporal swings in consumption mix. Typically these are regions that consume comparatively high levels of power from non-dispatchable nuclear, wind, and solar sources. On the occasions when such sources are not available, these regions then need to draw on electricity from dispatchable generators such as gas, coal and biomass. This leads to large changes in these regions' consumption emissions that are

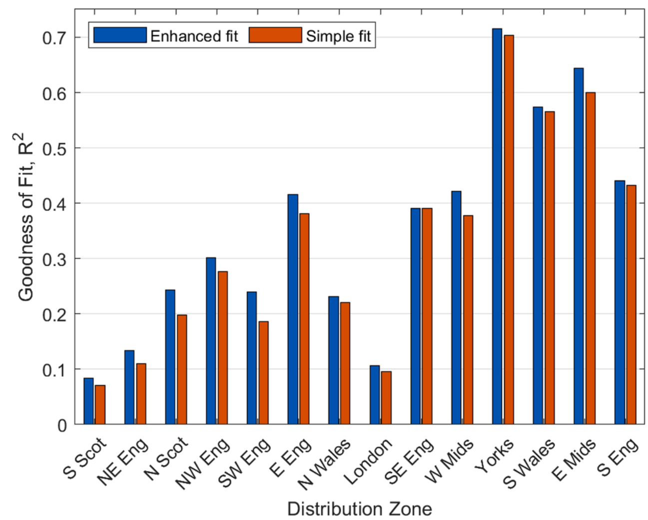

Fig. 3. Goodness of fits in each region of Great Britain over 2019.

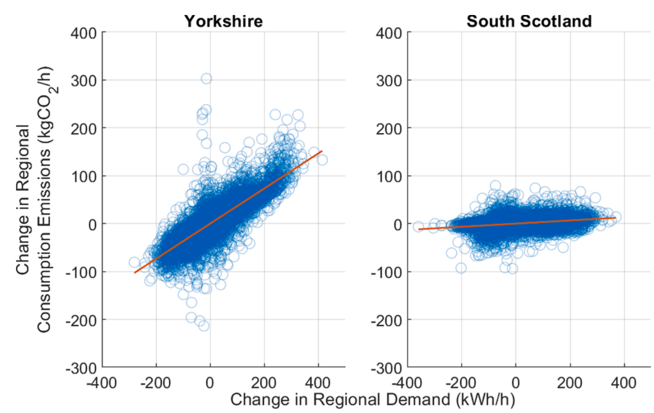

Fig. 4. Linear regression calculation of MEF in the regions with the highest and lowest R^2 values, Yorkshire and South Scotland respectively.

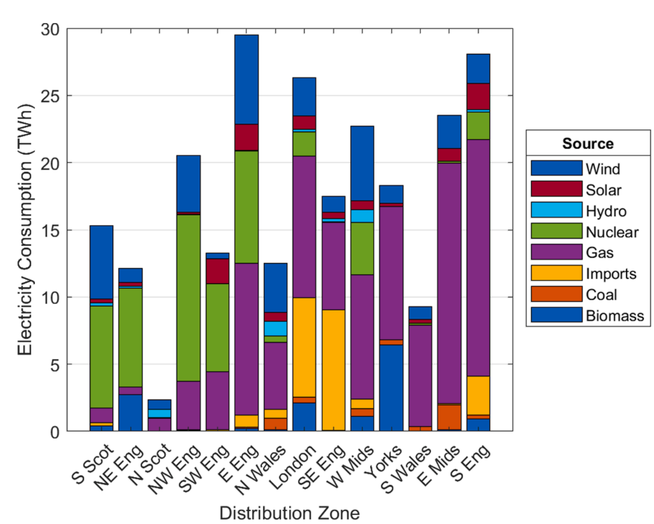

Fig. 5. Electricity consumption in each region of Great Britain over 2019, broken down by source.

uncorrelated with demand, because, say, gas generation is called upon to offset a drop in wind output.

By way of an illustration, Fig. 6 compares the extremes in the range of consumption mixes for Yorkshire ($R^2 \sim 0.7$) with those found in South Scotland ($R^2 \sim 0.1$). It can be seen that the consumption of electricity from zero carbon sources is very small in Yorkshire, with the vast majority of loads being met with dispatchable gas, biomass, and coal generation. Generally the generation mix remains relatively constant. In contrast, electricity demands in South Scotland are largely met using nuclear and wind generation, however electricity from gas (and, to a lesser extent, biomass) is consumed in winter during times of particularly high demand and low wind output.

Poor R^2 values do not invalidate the analysis presented as estimated MEFs still correspond to the time-average marginal emissions impact of changes in demand. Nevertheless, the poor fit does indicate that other (as yet unexplored) factors have a greater impact on emissions than demand, and using such data in our analysis would significantly underestimate the carbon-reduction potential of storage technologies in these regions. For this reason, we have excluded regions where the enhanced fit has an R^2 value smaller than 0.4.

3.4. Modelling electricity storage

We investigate the possible impacts of storage operation on CO_2 emissions by determining MEFs at times when storage is most likely to be operated. These are times of particularly low or high levels of system net demand (i.e. system demand net of wind and solar) and wind output. This approach broadly follows that introduced by McKenna *et al* to study national systems [8]. Three operating scenarios are implemented:

- Load levelling
- Wind balancing
- Reducing wind curtailment

In each scenario, MEFs are calculated for each region using the regression approaches developed in Section 3.2 but using subsets of the full data set, specifically data corresponding to times when national net demand or national wind output are in their upper or lower quartiles.

In the **load levelling** scenario, storage is charged when net demand is low and discharged when net demand is high. To model this, we separately calculate the MEFs for the times corresponding to the lower quartile of national net demand and the upper quartile of national net demand, with the means of the MEF time series being used in the enhanced regression approach.

In the **wind balancing** scenario, the storage is charged when wind output is high, and discharged when wind output is low, in order to smooth the output of wind farms. To simulate this, MEFs are separately calculated for the times corresponding to the upper and lower quartiles of national wind output.

In the **reducing wind curtailment** scenario, the storage is charged using excess wind generation that would otherwise be curtailed, and discharged when net demand is high. Excess wind has an MEF of zero, and the MEF for periods of high net demand is calculated using data from the times corresponding to the upper quartile of national net demand.

Our reducing wind curtailment scenario can be contrasted with the '(synchronous machine / wind-integrated) reducing wind curtailment' scenario used by McKenna *et al* [8], in which the storage is discharged at times of low wind output. It is expected that our scenario will give greater emissions reductions, because of the positive correlation

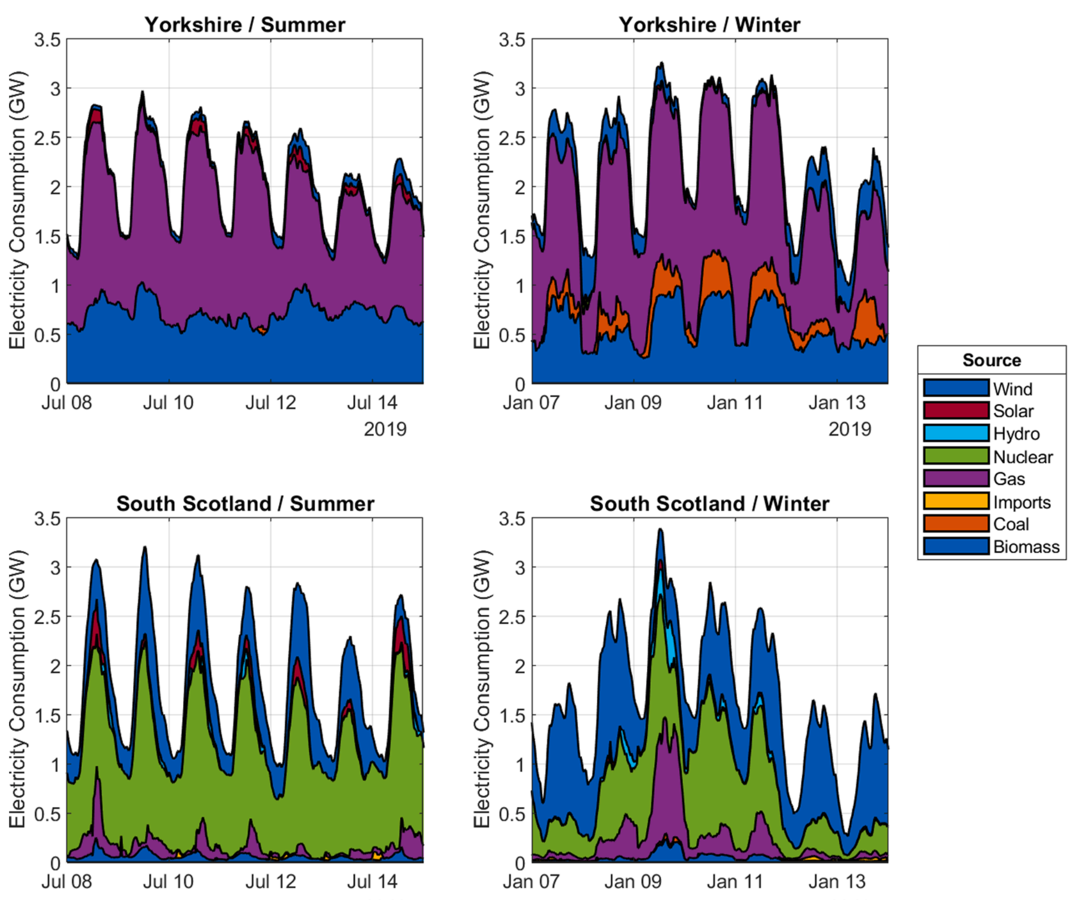

Fig. 6. Profiles of electricity consumption by source for Yorkshire and South Scotland over one week in mid-summer and mid-winter.

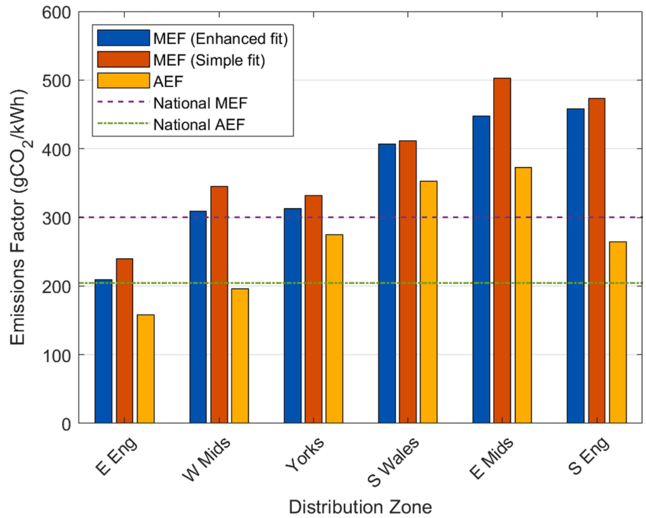

Fig. 7. Marginal and average emissions factors for selected distribution zones in Great Britain over 2019.

between system net demand and MEFs that is now seen at most levels of net demand in the GB electricity system, as shown in Fig. 2.

4. Results and discussion

4.1. Evaluating the regional MEFs

Fig. 7 shows MEFs calculated with both the enhanced linear regression and simple linear regression approaches presented in Section 3.2, for the six regions in which R^2 exceeds 0.4. Since the enhanced fit provides a time series of MEFs, the mean values are shown here. Regional AEFs are also shown for comparison, along with the national-level MEF (300 gCO_2/kWh) and AEF (204 gCO_2/kWh). The six selected distribution zones are listed alongside summary statistics in Table 2. These zones accounted for 52% of GB electricity consumption in 2019, and the two zones with the highest consumption (East England and South England) have the lowest and highest MEFs of the six when evaluated using the enhanced fit.

The regional MEFs span a considerable range, with enhanced fit values ranging from 209 gCO_2/kWh in East England up to 458 gCO_2/kWh in South England. The largest of these is over double the national average emissions factor. These findings clearly highlight the importance of considering emissions factors at a local level and using marginal rather than average emissions factors when assessing the impact on CO_2 emissions of an intervention in the energy system.

The areas with the highest MEFs are the industrial regions of South England, East Midlands, and South Wales. Of the regions with $R^2 > 0.4$, those with the lowest MEFs are East England, West Midlands, and Yorkshire, which consume high levels of nuclear, wind, and biomass power.

The enhanced fit gives lower MEF values than the simple fit in all selected regions, and the two approaches result in very similar values in most regions. In general terms, the differences appear to be larger in those regions that are more dependent on power imports from other regions. In such regions, changes in national demand have a relatively more pronounced impact on consumption emissions compared to changes in regional demand.

The general trend in the regional average emissions factors very broadly follows that of the marginal emissions factors. However, there are some regions, such as South England and the West Midlands, where differences between AEFs and MEFs are large.

Table 2
Selected Grid Supply Point (GSP) Groups and net take volumes over 2019.

Location	GSP Group ID	Net Take (TWh)	% of Total GB Take
E England	A	29.52	11.7%
W Midlands	E	22.73	9.0%
Yorkshire	M	18.29	7.3%
S Wales	K	9.30	3.7%
E Midlands	B	23.53	9.4%
S England	H	28.09	11.2%

4.2. Regional emissions from storage operation

To determine the effects of storage operation on CO_2 emissions we use the storage operating scenarios laid out in Section 3.4. Fig. 8 shows the results with the assumption of 100% turnaround efficiency, a value chosen to emphasise the importance of operating strategy and location over technology characteristics. National (GB) level results are also given.

The emissions associated with electricity storage operation vary considerably between regions and operating modes. The reducing wind curtailment scenario provides the greatest emissions reduction in all six regions. Emissions reductions are most pronounced in regions consuming high volumes of fossil fuel generation. Wind balancing generally provides the worst environmental performance, causing increased emissions in two areas. In the West Midlands, the performance of the wind balancing strategy appears particularly poor when viewed in light of the emissions reductions arising from the load levelling and reducing wind curtailment strategies. When considering that there is little coupling between electricity demand and wind power output, it becomes clear that storage operating in wind balancing mode will not necessarily reduce emissions unless it serves to reduce wind curtailment. Our reducing wind curtailment scenario, in which storage is discharged during periods of high net demand, provides greater emissions reductions than that used by McKenna *et al* [8], in which storage is discharged during periods of low wind output.

The load levelling scenario results in emissions reductions in all six regions, as well as for Great Britain as a whole. This can be contrasted with the findings of McKenna *et al* [8], which showed that load levelling always led to increased emissions. With reduced generation from coal power in Great Britain because of the Large Combustion Plant Directive and increased costs, MEF generally rises monotonically with net demand as shown in Fig. 2, and so storage operating in load levelling mode tends to reduce grid CO_2 emissions.

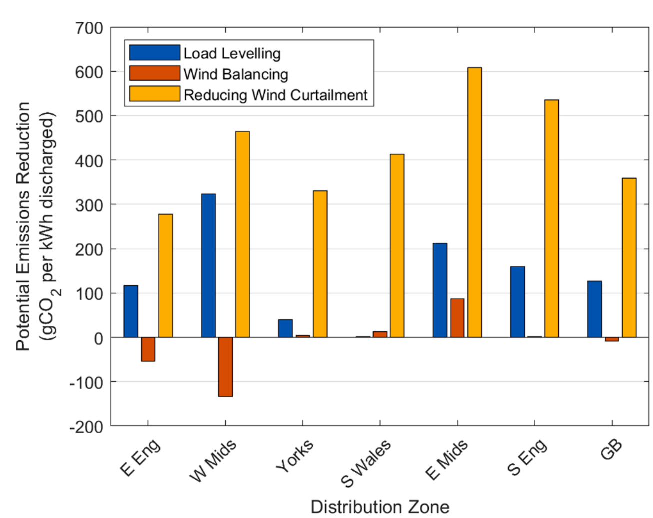

Fig. 8. Potential to reduce CO_2 emissions through electricity storage operation for three storage operating scenarios, in selected regions of Great Britain (GB) over 2019.

5. Conclusions

Electricity storage is a key technology for the long-term decarbonisation of power grids by facilitating the effective integration of variable renewables at large scale. The short-term impact of storage deployment and operation on electricity-related carbon dioxide emissions, however, has received scant attention in the literature. In this paper we have applied novel techniques to explore the potential impact of storage operation and geographical location on emissions from the electricity system of Great Britain. Our approach draws on recently released data to determine marginal emissions factors on a regional basis for 2019. Subsequently the marginal emissions factors are used to analyse the effect that a range of storage operation scenarios would have had on grid carbon dioxide emissions.

Our results show that specific scenarios could have radically different implications for emissions per unit of electricity delivered. Locating new storage in the East Midlands to manage wind curtailment, for example, provided a reduction in emissions of 608 gCO_2 per kWh passing though compared to the situation without that storage. In contrast, the same storage located in the West Midlands and used for wind balancing operations resulted in an emissions increase of 133 gCO_2 per kWh passing though. This difference of 741 gCO_2/kWh for a unit of electricity delivered is roughly equivalent to the reduction in emissions per unit achieved by fitting a coal power plant with carbon capture and storage and is significant.

Overall, operating storage to minimise wind curtailment maximised the carbon dioxide benefit in every region, with the wind balancing strategy consistently providing the poorest results. However, differences in regional characteristics were sufficient to offset this in some instances, with for example, the 'load levelling' strategy in the West Midlands giving a better emissions reduction than 'reducing wind curtailment' in East England. The 'reducing wind curtailment' approach generally produced greater benefits in regions with higher marginal emissions factors, as it allows the displacement of higher carbon generation.

We conclude that decisions regarding the location and operating strategy of new storage in Great Britain's current electricity grid could have a significant impact on the carbon dioxide benefits that are realised. As high carbon generation continues to be phased out the difference between the best-case and worst-case scenarios will decline in the future, but is likely to remain significant so long as there are still large variations in marginal emissions factors with system net demand and between regions. Policy makers and regulators should keep this in mind, ensuring that government support is directed towards schemes that will maximise emissions reductions.

Great Britain's electricity grid has been relatively successful in decarbonising over the last ten years, with many coal plant closing and average emissions factors declining. Despite this, variations in emissions factors are still sufficient to mean that storage operations have a significant impact on the carbon intensity of the electricity passing through. The same is likely to be true of other national electricity systems that have a mix of low carbon and fossil-based generation. Our methods have general applicability, and a follow-up study is currently aiming to identify optimal storage deployment and operational strategies for selected European countries with contrasting emissions factors. Our approach could also be used to investigate the carbon intensity impacts of other grid connected technologies, such as large-scale electrolytic hydrogen production or heat pump operation, and this forms a further line of enquiry.

CRediT authorship contribution statement

Andrew J. Pimm: Conceptualization, Methodology, Software, Validation, Data curation, Writing - original draft, Visualization, Project administration, Funding acquisition. **Jan Palczewski:** Methodology, Writing - review & editing, Supervision, Funding acquisition. **Edward R. Barbour:** Resources, Data curation, Writing - review & editing. **Tim T. Cockerill:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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.

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