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Evaluating the regional potential for emissions reduction using energy storage

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Abstract—Energy storage is an enabler of low carbon electricity generation, however several studies have shown that its use can cause a non-trivial increase in carbon emissions even if the storage has 100% round-trip efficiency. To understand the impact of storage operation and demand response on emissions, it is necessary to determine the marginal emissions factor (MEF) at the time the storage or demand response was operated. This paper presents statistical approaches to determining regional MEFs using data on regional electricity demand and generation by fuel type, with a simple power flow model used to determine consumption emissions by region. The technique is applied to the electricity system in Great Britain in 2018. It is found that the impact of storage varies widely by location and operating mode, with the greatest emissions reductions achieved when storage is used to reduce wind curtailment in areas which consume high levels of fossil fuel generation, and the greatest emissions increases occurring where storage is used for wind balancing in areas where wind is not curtailed. The difference between the highest emissions reduction and highest emissions increase is found to be significant, at 785 gCO_2 per kWh that passes through storage.

Keywords—emissions factors, decarbonization, storage, flexibility, demand-side response

I. Introduction

Energy storage is an enabler of inflexible, uncontrollable, and unpredictable low carbon electricity generation. In recent years, the costs of energy storage systems have fallen dramatically as a result of technology improvements, particularly in the area of electrochemical storage [1], and cost reductions are expected to continue into the future [2]. Energy losses associated with use of storage naturally result in an increase in greenhouse gas (GHG) emissions associated with all generation that passes through storage [3]. However, many studies have shown that use of storage to shift load from high demand hours to low demand hours, or to arbitrage on wholesale electricity prices, can cause a non-trivial increase in emissions even if the storage has a round-trip efficiency of 100% [4-8]. The effect of storage operation on emissions depends upon the marginal emissions factors (MEFs) at the times of charge and discharge, i.e. the effect of changes in load on system emissions. If charging storage causes an increase in generation from a relatively high carbon source (e.g. coal or gas), and discharging storage causes a decrease in generation from a relatively low carbon source (e.g. gas or renewables), then the net result is an increase in carbon emissions.

MEFs, which depend upon the marginal generating plant in a given period (e.g. half-hour), can be contrasted with average emissions factors (AEFs, also known as "carbon intensity"), which are a function of the generation mix in that same period. To understand the effect on carbon emissions of an intervention such as operation of storage or implementation of energy efficiency or demand response measures, MEFs should be used, since use of AEFs would unrealistically imply that all generating plant modify their output by the same proportion in response to a change in load. Since MEFs can be hard to determine accurately, particularly in systems like Great Britain's that do not follow the conventional approach of centralised 'optimal dispatch', AEFs are often used in carbon accounting [9]. However, several studies have shown that use of AEFs may grossly misestimate the avoided (or additional) emissions resulting from an intervention [10-13].

MEFs can be calculated over a range of timeframes. Long-run MEFs [14] are used to understand the effect of long-term changes to demand, such as the impact on particular infrastructure investment decisions, while short-run MEFs are used to understand the effect of short-term changes to demand (such as those arising from operation of storage). In this study we investigate the impact of storage operation on emissions, focusing on short-run MEFs.

Two main approaches have been used to develop short-run MEFs: 1) economic dispatch models, and 2) statistical models based on empirical data. Economic dispatch models typically use a merit order based approach, with the assumption that generators are dispatched in order of marginal cost, where the last generator needed to meet demand sets the marginal emissions rate for the system [12]. Dispatch models have been used to derive MEFs in the US [15-17] and Europe [10, 18, 19], often using generator utilisation (i.e. capacity factors) as a proxy for variable operating cost and hence position in the merit order. Statistical models typically use linear regressions of historical data to determine MEFs. In Great Britain, this approach was used by Hawkes on half-hourly system data from 2002-2009 [11] (building on foundations laid by others [20, 21]) and by Thomson et al to understand the avoided emissions from use of wind power from 2009-2014 [22]. Linear regression has also been used to determine MEFs for Ireland [8], the US [6, 7, 12, 13, 23], and Portugal [24].

Li et al [7] conducted an in-depth study of MEFs in the US Midcontinent Independent System Operator (MISO) system, giving special attention to the effects of renewables. Using a statistical approach, an “expanded MEF” was developed which accounts for generation from both emitting and non-emitting sources, and this was contrasted with “conventional MEFs” which do not include non-emitting sources. The authors also made use of 5-min fuel-on-the-margin data published by MISO. It was found that when renewables penetration becomes high with sufficient dispatchability, accounting for emitting sources only significantly overestimates MEFs, and underestimates the emissions increases arising from using storage to load shift from high demand hours to low demand hours. Since the penetration and dispatchability of renewables varies by location, energy policies based on MEFs would benefit from specific consideration of sub-regional differences in consumption and fuel mix.

The importance of location has been noted in several other studies [6, 12, 25]. Hittinger and Azevedo [6] estimated the effect of bulk storage on net emissions in 20 sub-regions in the United States, finding that net system CO_2 emissions resulting from storage operation range from 104 to 407 gCO_2/kWh of delivered energy depending upon location, storage operation mode, and assumptions regarding carbon intensity. Tranberg et al [25] developed a real-time carbon accounting method for the European electricity market, employing a flow tracing methodology to track the flow of electricity by generation technology and country of origin. Differences in production and consumption intensities were found to be large in countries that import power from countries with different generation mixes to their own. By way of example, Austria’s generating capacity is largely dominated by hydro, so it has a low production intensity of 136 gCO_2/kWh, however it relies heavily on imported coal power from Poland and the Czech Republic, and so its consumption intensity is 82% higher than its production intensity, at 248 gCO_2/kWh.

In Great Britain, National Grid manages the Carbon Intensity Tool [26], a website/API providing data on the carbon intensity of electricity generation (i.e. AEFs) in Great Britain. This provides both national AEFs and regional AEFs, with the regional breakdown achieved using a power flow model.

Sun et al [27] developed an emissions arbitrage algorithm to improve the environmental performance of domestic PV-battery systems. Focusing on Great Britain, this projected future time-varying MEFs out to 2050 and examined the environmental benefits of arbitraging on carbon emissions using a simple threshold-based charge-discharge strategy, i.e. charging the battery when MEF is below a lower threshold, and discharging the battery when MEF is above an upper threshold. It was found that the CO_2 saved relative to the same system with PV only can more than pay back the CO_2 debt of manufacturing the battery, as long as Great Britain moves away from the present-day situation where natural gas-fired generators are nearly always the marginal generator.

In this paper, we focus on the regional differences between MEFs, and the impact that location might have on the effectiveness of storage for reducing CO_2 emissions. To accomplish this, we develop two statistical approaches to calculating regional MEFs, then apply these techniques to Great Britain in three different storage operating scenarios.

II. METHODOLOGY

A. Determining Regional Marginal Emissions Factors

In developing a statistical approach to the determination of regional MEFs, we bring together three key pieces of work: the statistical regression approach to determining MEFs introduced by Hawkes [11]; the spatial resolution of power flows and consumption emissions of Bruce and Ruff [26]; and the multiple linear regression (MLR) approach to determining the marginal displacement factor of wind developed by Thomson et al [22].

To determine the impact on carbon emissions of a change in a specific region’s electricity demand, it is first necessary to approximate the region’s consumption-based emissions, i.e. the emissions caused by that region’s electricity consumption, taking the distribution of demand and generators into account along with the interconnection between regions. For this purpose, a power flow model is necessary to determine flows in the electricity transmission network and hence associate electricity consumption with generation. This approach has been applied in Great Britain by Bruce and Ruff on behalf of the system operator [26] and in continental Europe by Tranberg et al [25]. Both the work of Bruce and Ruff and that of Tranberg et al are used in the development of websites, the former for the Carbon Intensity website and API (www.carbonintensity.org.uk) and the latter for electricityMap (www.electricitymap.org).

The Carbon Intensity API provides historical and forecasted regional carbon intensity data, and we make use of the historical data here. It is built on a reduced network model of Great Britain, which is used to calculate the CO_2 transfers between importing and exporting regions, accounting for the impedance characteristics of the network, constraints, and system losses. Carbon intensity factors are given in Table I.

TABLE I. CARBON INTENSITY FACTORS FOR EACH FUEL TYPE [26]

Fuel Type	**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

MEFs are typically calculated using the regression approach developed by Hawkes [11], whereby the differences between half-hourly carbon emissions from transmission-connected generators (y, in gCO_2/h), in Hawkes's case within Great Britain over the period 2002-2009, are plotted against the corresponding differences in half-hourly national electricity demands (x, in kWh/h), with a line of best fit of the form $y = mx$ giving the MEF (m, in gCO_2/kWh).

To perform this regression on a regional basis, regional half-hourly electricity demand data is required. The high voltage electricity transmission network in Great Britain is connected to the lower voltage distribution network at nodes known as "grid supply points" (GSPs), and the distribution network is split into 14 different distribution zones by grouping GSPs on a regional basis, to form 14 GSP groups. Half-hourly electricity "take volume" data for each of the 14 GSP groups (i.e. the flow between the transmission network and distribution network for each group) is made available by Elexon and is known as the CDCA-I029 report, part of the P114 dataset.

To determine the marginal impact of a region's electricity demand on its consumption-based carbon emissions, we should ideally separate the effect of changes in the region's demand from the effect of changes in national demand (which can cause changes to the generation mix in nearby regions). Fig. 1 shows a scatter plot of regional consumption-based carbon emissions for the South Wales distribution zone (GSP group ID: K) against electricity demand in that region and national electricity demand. A planar surface is fitted to the data, of the form

$$\Delta C_i = a_i \Delta D_{r,i} + b_i \Delta D_n + c_i \qquad (1)$$

where ΔC_i is the change in regional consumption-based emissions in region i, $\Delta D_{r,i}$ is the change in regional demand, and ΔD_n is the change in national demand. The coefficients a_i, b_i and c_i are found through MLR. The regional consumption-based emissions C_i for Great Britain are calculated by multiplying the regional carbon intensity data (from the Carbon Intensity API) by the CDCA-I029 regional demand data.

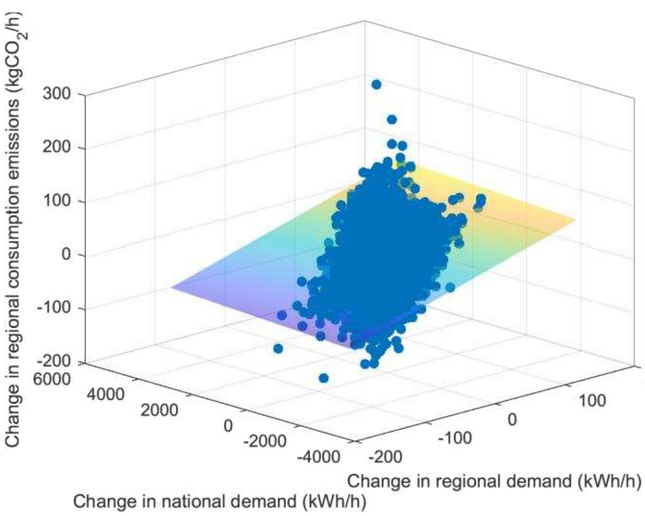

Fig. 1. Change in regional consumption emissions in South Wales against change in regional demand and change in national demand, over the period 11th May 2018 to 13th January 2019.

Since the historical carbon intensity data is only available from 11th May 2018 and, at the time of writing, the regional electricity demand data is only available up to 13th January 2019, the analysis presented here covers the period 11th May 2018 to 13th January 2019.

To determine the marginal impact of changes in the region's electricity demand, we are interested in what happens to the region's consumption-based emissions when a change in regional demand is equal to the change in national demand, i.e. when $\Delta D_{r,i} = \Delta D_n$. The regional MEF, m_i, is thus given by

$$m_i = a_i + b_i \qquad (2)$$

The MLR approach is compared against regional MEFs calculated using a two-dimensional linear regression approach, whereby a line-of-best-fit of the form $y = m_i x$ is fitted to a plot of change in regional consumption-based emissions (ΔC_i) against change in regional demand ($\Delta D_{r,i}$). An example of this is shown in Fig. 2.

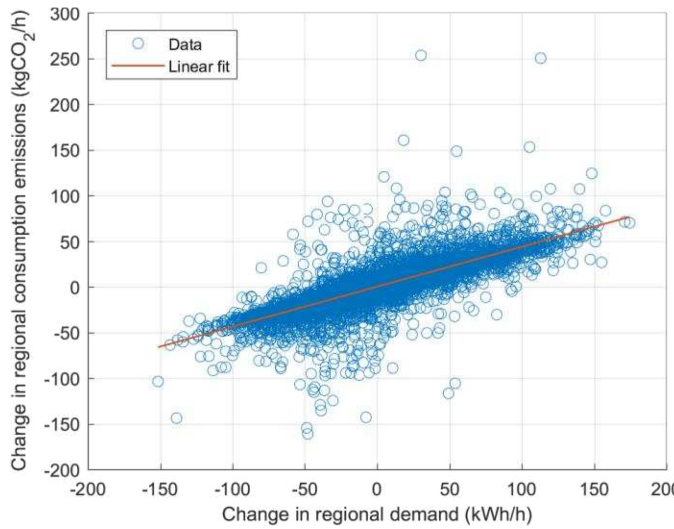

Fig. 2. Development of regional MEF using a two-dimensional linear regression approach, for South Wales over the period 11th May 2018 to 13th January 2019.

B. Storage Operating Scenarios

To evaluate the impact of energy storage operation on carbon emissions, we consider three operating scenarios:

1. Load leveling
2. Wind balancing
3. Reducing wind curtailment

For the load leveling scenario, it is assumed that storage is charged during periods with low net demand and discharged during periods of high net demand. To accomplish this, we separately calculate the MEFs for the times corresponding to the lower quartile of net demand and the upper quartile of net demand. Net demand is calculated as system demand minus wind output, where system demand is calculated by summing the CDCA-I029 regional take volume data and wind output data is taken from the BM Reports website/API.

For the wind balancing scenario, it is assumed that storage is charged during periods when wind power output is highest, and discharged during periods when wind power output is lowest, in order to smooth wind power output. To accomplish this, MEFs are separately calculated for the times corresponding to the lower and upper quartiles of wind output.

For the reducing wind curtailment scenario, we make the assumption that storage is charged using excess wind power that would otherwise be curtailed, and discharged during periods with low wind power output. Excess wind power has zero MEF, and the MEF for periods of low wind power is calculated for the times corresponding to the lower quartile of wind output.

III. Results

Using the MLR methodology laid out above, the regional MEFs for the 14 distribution zones of Great Britain are determined and shown in Fig. 3 ("3D fit"). For comparison we also show the regional MEFs as calculated using a simple two-dimensional linear regression of regional consumption-based emissions against regional demands ("2D fit"), and the regional AEFs. Distribution zone IDs are given alongside summary statistics in Table II.

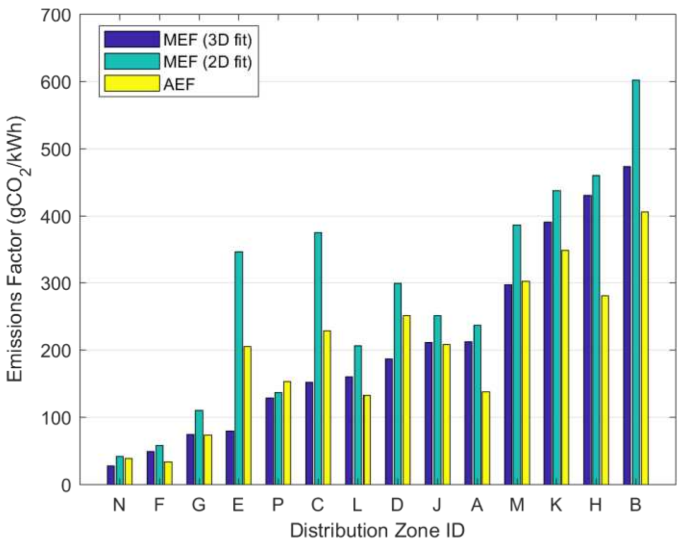

Fig. 3. MEFs for the 14 distribution zones in Great Britain over the period 11[th] May 2018 to 13[th] January 2019 as developed using the multiple linear regression approach (3D fit), along with MEFs developed using a two-dimensional linear regression approach (2D fit) and AEFs.

From Fig. 3, it is clear that regional MEFs span a significant range, from 28.8 gCO_2/kWh in East Midlands up to 468.5 gCO_2/kWh in South Scotland. The three regions with the highest regional MEFs are East Midlands, South England, and South Wales, and the three regions with the lowest regional MEFs are South Scotland, North East England, and North West England.

In comparing the MLR approach with the two-dimensional linear regression approach, it is clear that the two-dimensional approach gives higher values in all regions, and that the two approaches give very similar results in all but a small number of regions. The most noteworthy exceptions are zones E (West Midlands), C (London), and D (North Wales). In the most extreme case, West Midlands, the two-dimensional approach gives a value of regional MEF that is four times that calculated using the MLR approach.

TABLE II. GSP groups, along with net take volumes over the period 11[th] May 2018 to 13[th] January 2019

ID	Location	Net Take (TWh)	% of Total
A	E England	18.07	11.4
B	E Midlands	14.44	9.1
C	London	17.51	11.1
D	N Wales	8.21	5.2
E	W Midlands	14.32	9.1
F	NE England	7.85	5.0
G	NW England	13.25	8.4
H	S England	17.84	11.3
J	SE England	11.31	7.2
K	S Wales	5.78	3.7
L	SW England	7.24	4.6
M	Yorkshire	11.70	7.4
N	S Scotland	9.05	5.7
P	N Scotland	1.46	0.9
	Total	**155.15**	

As expected, differences between the two approaches are most pronounced in regions where the impact of national demand on the region's consumption emissions, b in (1), is high relative to the impact of regional demand, a. Unlike the two-dimensional approach, the MLR approach focuses on the changes in regional demand which cause corresponding changes in national demand, ensuring that the calculated value of regional MEF is not confused by changes in demand elsewhere on the system. However, as explained further on, it sometimes gives negative values of MEF, so should be used with caution.

It can also be seen that the regional average emissions factors are approximately similar in magnitude to the corresponding marginal factors. From the perspective of charging for emissions, which would most likely need to be done based on average emissions factors rather than marginal emissions factors, this is reassuring.

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, the source of electricity consumed in each region is calculated and shown in Fig. 4. It becomes clear that the low AEFs in regions such as South Scotland (zone ID: N), North East England (F) and North West England (G) are a result of the presence of wind, with several large onshore wind farms located in the Scottish Lowlands, and nuclear, with two plants in South Scotland and one in each of North East England and North West England.

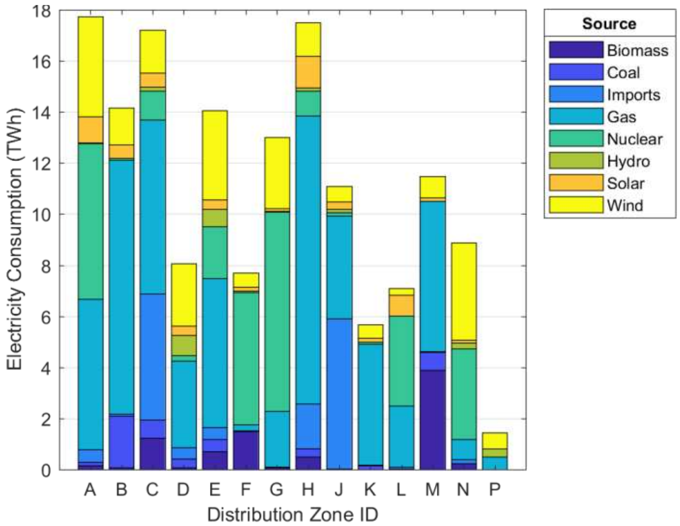

Fig. 4. Fuel types consumed in each region of Great Britain over the period 11th May 2018 to 13th January 2019.

To evaluate the impact of storage operation on carbon emissions we use the storage operating scenarios outlined in the previous section. The two-dimensional MEF calculation method is used, because the MLR approach sometimes gives negative values of MEF. The results are shown in Fig. 5 for the case of 100% round-trip efficiency. GB-level results are also shown. It can be seen that the impact of storage operation on carbon emissions varies widely depending upon location and the storage operating mode. The reducing wind curtailment operating scenario achieves the highest emissions reductions in all but three regions, and reductions are greatest in areas which consume high levels of fossil fuel power. Emissions reductions are lowest in the wind balancing operating scenario, with eight of the fourteen regions showing increased emissions. Wind balancing in the West Midlands (E) and North Scotland (P) appears particularly negative when compared with the savings that could be achieved using either of the load leveling or reducing wind curtailment scenarios.

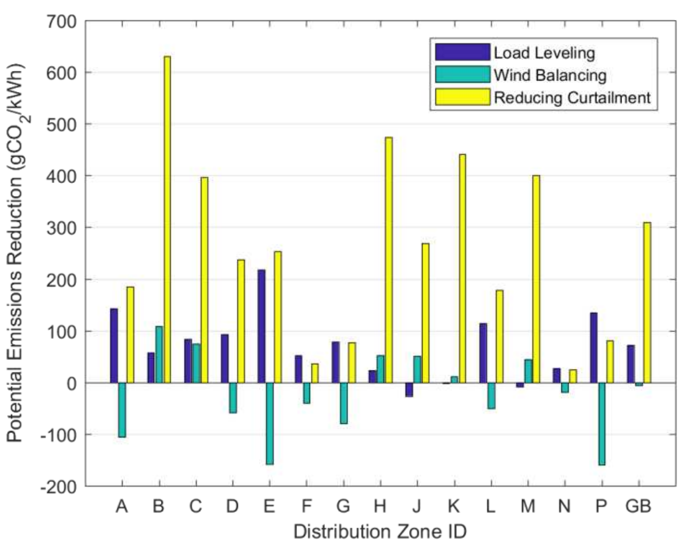

Fig. 5. Potential emissions reductions from operating electricity storage in each region of Great Britain over the period 11th May 2018 to 13th January 2019, for three different storage operating scenarios.

The load leveling scenario results in emissions reductions in all but three regions. This can be contrasted with the findings of McKenna et al [8] in their study of the All-Ireland power system, where it was found that load leveling always caused an increase in emissions. With reduced levels of coal generation in Great Britain as a result of a higher costs and the effects of the Large Combustion Plant Directive (reduced running hours and plant closures), MEF generally rises monotonically with net demand in Great Britain, and so load leveling provides emissions reductions.

IV. Discussion and Conclusions

This paper has developed two approaches to determining regional marginal emissions factors based on a power flow model and historical generation and demand data. These approaches were used to determine the impact of energy storage operation on carbon emissions across the different regions of Great Britain in 2018. It has been found that the emissions associated with storage operation vary widely between regions and operating modes, with the highest emissions reductions being achieved when storage is used to reduce wind curtailment in areas which consume high levels of fossil fuel generation (such as East Midlands, South England and South Wales). Emissions increases are most likely when storage is used for wind balancing in areas where there is no wind curtailment.

The highest emissions reduction, at 630 gCO_2/kWh, is achieved through reducing wind curtailment in East Midlands, and the difference between this and the highest emissions increase (wind balancing in West Midlands or North Scotland) is over 780 gCO_2 per kWh that passes through storage. This is significant and, per kWh of electricity delivered, is similar in scale to the replacement of coal power with biomass. In the UK, the government has committed to phasing out unabated coal power by 2025, so such high levels of emissions reductions from storage operation will no longer be achievable at that point, however until all power generation comes from zero carbon sources it will remain the case that storage operation will have an impact on carbon emissions, and that that impact will vary by geographic location. Also, as the penetration of variable and inflexible generation increases, there will be more opportunities for storage to reduce emissions. It is anticipated that the methods presented in this paper will be particularly useful in countries and regions with high levels of generation from fossil fuels, and future work could consider different electricity systems.

To encourage siting and operation of storage such that it has the greatest positive impact on emissions reduction in liberalised electricity markets, it is important that a strong carbon price is set, and that the price paid for electricity reflects the carbon intensity of the electricity being consumed. To fully implement this approach would require regional, time-dependent electricity prices.

We note that the results in this paper are limited by several factors. Firstly, the results for Great Britain have been generated using only eight months of data; it is anticipated that the research will be extended using at least two years' worth of data when more carbon intensity data are made available in the Carbon Intensity API, improving the accuracy of the results. Secondly, the emissions factors are calculated quite simply, and could be enhanced with generator-level data and part-load thermal efficiencies. Thirdly, the analysis is based on historical data, and does not consider possible future changes to the generation mix. It would be worth looking at future energy scenarios in extensions of this work.

Other future work in this area could consider the impact of carbon prices on the operation of storage and resulting carbon emissions, and the interplay between economic and environmental objectives. It would also be worthwhile to use regional marginal emissions factors to understand the potential for emissions reductions through demand response, such as smart charging of electric vehicles and enhanced heat pump operation.

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