Daily marginal CO₂ emissions reductions from wind and solar generation

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Abstract— This paper estimates the half-hourly and daily CO₂ emissions from electricity generation in Britain, and the influence that wind and solar output has on these. Emissions are inferred from the output of individual plants and their expected efficiency, accounting for the penalty of part-loading thermal generators. Empirical Willans lines are created for typical coal, oil and combined-cycle gas generators from the US CEMS database, giving the first fully-empirical treatment of the British power system. We compare regressions of half-hourly and daily emissions to estimate the impact of plant start-ups, which may not occur in the specific hours when wind and solar output drops, and thus may be mis-identified in half-hourly regressions. Our preliminary findings show that dynamic plant efficiency may reduce the carbon savings from wind by 5-12% and for solar by 0-6%. The effect is strengthening with increasing penetration.

Index Terms—carbon emissions; solar energy; wind energy; wind energy integration.

I. INTRODUCTION

In order to tackle climate change, worldwide energy systems are increasingly deploying low carbon technologies, such as wind and solar. However, the question of how much CO_2 is saved by building e.g. one megawatt of wind power is far from trivial. Currently, average emission factors (AEF) for the entire energy system are widely used. These average the emission of all power plants over time and space, implicitly assuming that wind power will displace an equal share of all technologies on the system, which is plainly incorrect. Nuclear reactors do not reduce output and solar panels do not become shaded when the wind blows.

Marginal emissions factors (MEF) can be calculated by identifying the stations that change operation in response to changes in wind output, and give a more accurate answer. The study of MEF is more data intensive as it requires the knowledge of the state of individual power stations. However, its results are of more use to policymakers as it provides a higher level of accuracy and determines the amount of wind and solar on the system to obtain CO_2 emissions reduction.

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II. PROBLEM

Adding wind and solar farms into a power system will reduce the capacity factor of conventional plants, and the variable output of these farms will force conventional generators to run in more dynamic operating modes, with increased start-ups and ramping events. Some argue this will have negative effects on overall carbon emissions, as this will lower the efficiency and thus increase the carbon intensity of conventional generators. Understanding of this area is far from clear, which risks undermining support for renewables as a means of decarbonisation.

A. Conclusions from the literature

Existing studies (of Texas and Great Britain) show that marginal emissions may differ significantly from AEF based calculations. Several authors have considered the marginal emissions factors for wind power in specific case studies (e.g. Texas, Britain). However, these studies are based on hour-tohour changes in generation, potentially neglecting the fact that the set of power stations scheduled to operate throughout a day may depend on the expected wind output.

The first study of marginal emissions based on actual generator behaviour that we are aware of is [1], which calculated the half-hourly changes in generation from 2002 to 2009 at each large power station in Great Britain and multiplied these by the annual average emissions per kWh for 11 generator types. This gave an MEF of 0.69 kgCO₂/kWh, compared to an AEF of 0.51 kgCO₂/kWh. Thomson et al. [2] point out that the assumption of constant emissions per kWh ignores changes in efficiency as each generator's load changes, and therefore derived load-specific emissions factors for a coal-fired and a Combined Cycle Gas Turbine generator. When these were applied to the actual outputs of power stations in Great Britain, the MEF of changes in demand varied from 0.49 kgCO₂/kWh in 2013 to 0.66 kgCO₂/kWh in 2009; the AEF varied between 0.47 kgCO₂/kWh (in 2014) and 0.55 kgCO₂/kWh (in 2012). Thomson et al. [2] also calculate the marginal displacement factors for changes in wind power and calculates that wind generation saved 35.8 MtCO₂eq from 2009-14, as opposed to 32.4 MtCO₂eq based on AEFs.

US studies have the advantage of hourly emissions data gathered by the Continuous Emission Monitoring Systems program, CEMS. Siler-Evans et al. [3] estimate MEFs for 8 regions of the US, with a range from 0.49 kgCO₂/kWh to 0.83 kgCO₂/kWh. Kaffine et al. [4] use data from Texas and estimates the impact of wind generation econometrically, based on actual emissions and controlling for load, temperature and time of day and seasonal patterns. The marginal displacement factor is 0.47 kgCO₂/kWh. Kaffine and McBee [5] show that emissions fall by 15% less in hours with the highest decile of this variation.

B. Expected results from this work

The novelty of this study lies in combining two richlydetailed datasets of power station operation to gain the best estimate of half-hourly CO_2 emissions from the British generation fleet, based entirely on empirical data rather than assumptions or generalisations. The British balancing and settlement code company (Elexon) provides the half-hourly electricity generation from each individual unit, but this does not measure emissions released. We therefore combine it with US CEMS data on the generation, fuel consumption and emissions of individual power stations. We match units from the two databases together, to give an estimate of the halfhourly emissions that could be expected for the given operating patterns of the British units.

The work undertaken will increase the understanding of the interaction between wind and solar and their contribution to carbon emissions reductions in the British (GB) energy system. The presented methodology allows us to present results based on real data that considers part-loading of all major power stations in GB.

III. DATA

For the British power station output, we use the Elexon P114 dataset [6] which gives half-hourly observations from 234 generator units (including 63 coal and 86 gas) over the period Nov-2008 to Dec-2017 (a total of 41 mil observations). The summed output of all generators from each fuel type was checked against the Elexon aggregated-fuel totals [7] and found to give good agreement. We take the registered capacity of each unit and normalise its output to generate time-series of capacity factors

To estimate emissions as a function of capacity factor, we use data from the Continuous Emissions Monitoring System (CEMS) database from the US EPA [8]. This provides the hourly capacity factor and carbon intensity (kg/kWh) for individual power station units across the US. Data were compiled from 2001 to 2010 for all fossil types. Stations that match the characteristics of the British generator fleet were isolated (primarily subcritical coal stations built between 1960 and 1984, and CCGTs built between 1990 and 2008).

The default carbon emissions intensity for each power plants type is stated below. It is used for all power plants for which individual efficiency was not available. For 87 units out of 234, specific emissions factors are known and are applied instead of the default carbon intensities below.

 TABLE I.
 DEFAULT CARBON INTENSITIES IN THE GB ELECTRICITY SYSTEM

Carbon intensity of plants type in kg/kWh							
Coal	Gas	Peaking	Wind/Solar/ Hydro/Nuclear	Biomass	French Interconnector	Dutch Interconnector	Irish Interconnector
0.936	0.394	0.651	0.0	0.120	0.053	0.474	0.458

IV. METHODOLOGY

To estimate the marginal carbon emissions reductions from wind and solar in the GB energy system, several steps are necessary. The methodology explains the calculation of the marginal carbon emissions, later called the dynamic case. At the end of the chapter, a base case for comparison is established, based on the same data.

The unique identifier for each of the series in [6] was matched against a list from the GB balancing entity Elexon [9]. In most cases this allows to define the unit as a generator or consumer, its clear name, and its import/export capacity over time. In some cases, the plant type is codified in the BM unit name, which determine whether the unit is a wind farm, railway demand and so on. This is generally not true for fossilfired power stations. The step identified in total 234 power stations, double-counting the conversion of coal-fired power plants to use biomass. Installed capacities are also obtained from the time series of each data set, using their 95% and 99% quantiles of generation.

The clear names from the previous step allows the matching of the 234 generation units against the PLATTS database, which contains 5883 power plants for the GB power system. The matching uses the Damerau-Levenshtein and Jaro-Winkler fuzzy string-matching algorithms and the indicated capacity in Elexon BM unit data to identify possible matches between the two lists of power plants. Where necessary, names where matched manually.

The matching with the PLATTS database allows the identification of each plant type (i.e. CCGT, OCGT, Coal) and its attributes (e.g. year of first generation). This step can be carried out since the plants characteristics are mostly defined by its technology, age and capacity, and not by its location in certain parts of the world. For each Elexon unit a list of similar US based power plants is identified in PLATTS. This is achieved by selecting units that are of the same type (e.g.: OCGT, CCGT, Coal subcritical, etc.) and are not more than five years older or younger. Due to low data availability the range for biomass is extended to ± 10 years and to ± 15 years for oil-fired gas turbines. Additionally, the installed capacity is used as selection criteria which shall not deviate by more than 50% from the capacity identified for each Elexon unit.

The next step identifies matches between the names for the available CEMS data and the PLATTS database, using fuzzy string-matching and power plant characteristics. Using CEMS data requires significant effort to address irrelevant or false data points to avoid false results due to data artefacts. Each CEMS data set contains values for each hour (t) (for each time steps in the CEMS data set) on the plants power output ($P_{El}(t)$ in MW), its fuel burn ($F_{Fuel}(t)$ in kWh), production of electric energy ($E_{El}(t)$ in kWh), and the mass of the SO₂, NO_x and CO₂ emitted ($T_{CO2}(t)$ in kg). The efficiency of each plant at the time t is defined as following:

$$Eff = E_{El}(t)/F_{Fuel}(t)$$
(1)

Furthermore, the specific carbon emission (S_{CO2} in kg/kWh) of each plant at the time t is:

$$S_{CO2} = T_{CO2}(t) / E_{El}(t)$$
 (2)

For each CEMS plant a non-parametric regression of the efficiency Eff against the hourly capacity factor C(t) and the specific emission S_{CO2} against the hourly capacity factor C(t) is carried, using both LOESS (blue line below) and smoothing splines (coral line). The result can be seen below for an exemplary coal plant.



Figure 1. Specific carbon intensity in relation to plant loading for a single unit in the CEMS data set.



Figure 2. Efficiency in relation to plant loading for a single unit in the CEMS data set.

Applying these regressions to the GB power plants requires the normalisation of the curve to one at nominal load of the plant. The current state of research suggests, that results are better when full load emissions factors ($S_{CO2,FL}$ in kg/kWh) for each GB plant are taken from other sources rather than implied by the CEMS data. The regression as shown above will serve as a multiplier $M_{CO2}(t_2)$ to calculate to the specific carbon emission for each half-hourly time step of the plant $S_{CO2,PP}$ (in kg/kWh).

$$S_{CO2,PP}(t_2) = C(t_2) * S_{CO2,FL} * M_{CO2}(t_2)$$
(3)

Multiplying this with the energy produced $E_{el,ELEXON}(t_2)$ (in kWh) for each Elexon unit, this yields total carbon emissions $T_{CO2,PPn}(t_2)$ for each half-hourly time step.

$$T_{CO2,PPn}(t_2) = S_{CO2,PP}(t_2) * E_{el,ELEXON}(t_2)$$
 (4)

Finally, all carbon emissions from the fossil generators are summed up, together with the carbon emissions from other types of generation, applying a constant carbon intensity to nuclear, biomass, hydro generation as well as to the Irish, French and Dutch interconnectors.

From this complete data sets, hour-to-hour differences are calculated for the change in carbon emissions, demand $D_D(t_2)$, wind $D_W(t_2)$ and solar output $D_S(t_2)$. This allows to calculate the hourly marginal emissions factor $D_C(t_2)$ and the coefficients for the parameters of the linear regression α_W , β_S and γ_D .

$$D_{C}(t_{2}) = \alpha_{W} * D_{W}(t_{2}) + \beta_{S} * D_{S}(t_{2}) + \gamma_{D} * D_{D}(t_{2})(5)$$

The daily marginal emission $D_C(t_2)$ are calculated for each time period of 48 half-hourly steps $t_{2,1...n}$ (for each time steps in the Elexon data). Building the daily average allows the correction of inaccuracies that may be caused by possible time lags, due to a timely offset of energy generation and fuel burn in start-up and shutdown events.

$$D_{C}(T) = \alpha_{W} * \frac{1}{48} \sum_{t_{2}=1}^{48} D_{W}(t_{2}) + \beta_{S} * \frac{1}{48} \sum_{t_{2}=1}^{48} D_{S}(t_{2}) + \gamma_{D} * \frac{1}{48} \sum_{t_{2}=1}^{48} D_{D}(t_{2})$$
(6)

The marginal emissions reductions that account for the part load of plants need to be compared to a base case. The base case uses the same data set, however simplifies the carbon emissions calculations by multiplying the station output by the fixed carbon emissions factors in Tab. 1.

V. PRELIMINARY RESULTS

In the course of the investigation the CEMS data set has turned out to be more challenging than anticipated. Initially it was planned to use a regression of a combination of suitable power plants from the CEMS data set to extract information on carbon intensity and efficiency directly. However, even with thorough selection of power plants and data cleaning, the results at this stage would have led to inconclusive results. For this paper, assumptions on plant efficiencies were necessary. This means that plant efficiencies were used as described in Tab. 1, or derived from secondary sources for individual power plants.

The results from the calculations using our new approach with part-loading of power plants and the base scenarios are based on the same data set. The half-hourly total emissions from both approaches are shown in Fig. 3 below. If both approaches had produced the same results, all the points would lie along the blue line. From the results below, one can observe a deviation from the base case. This shows that including the part loading of power plants in the assessment has a noticeable impact on the carbon emissions.



Figure 3. Deviation of total half-hourly CO₂ emissions between the base case and the dynamic case.

Having established the difference between the flat carbon emissions factors in the base case and the impact of part-loading of power plants in the dynamic case, we can calculate regressions for the base case and the dynamic case. The graph below depicts the change in carbon emissions over the change in residual demand (Demand less the output from wind & solar) for all years. The coral dots show the base case, whereas the green dots show the dynamic case, both with their linear regression.



Figure 4. Regression of change in carbon emissions against the residual load for the base case and the dynamic case.

The marginal carbon abatement from wind and solar is derived from the coefficients of the regression α_W , β_S and γ_D of the half-hourly data for the base case and the dynamic case are shown in the table below. Data points are chosen for the entire data, as well as the years 2012, 2014 and 2017. This

allows the comparison with results from the literature. It should be noted that the results may be sensitive when using different data sources. Therefore, caution may be necessary when comparing the results with the numbers in the literature.

The overall calculated total carbon emissions in 2017 in the base case were 67.5 Mt, in the dynamic case 68.5 Mt. The half-hourly carbon emissions from both cases are shown in Fig. 3.

 TABLE II.
 Regression parameters of the half-hourly

 MARGINAL CARBON EMISSIONS FOR THE BASE CASE AND THE DYNAMIC CASE

Half-hourly marginal emissions factors in kg/kWh							
	All years	2012	2014	2016	2017		
Base case							
Solar β_S	-0.471	-0.380	-0.345	-0.422	-0.382		
Wind α_W	-0.438	-0.476	-0.442	-0.402	-0.363		
Demand γ_D	0.482	0.480	0.448	0.409	0.390		
Dynamic case							
Solar β_S	-0.470	-0.463	-0.357	-0.408	-0.364		
Wind α_W	-0.391	-0.446	-0.401	-0.337	-0.294		
Demand γ_D	0.462	0.467	0.427	0.380	0.356		

This means that for all years the change in solar by 1 kWh of solar, emissions are reduced on average by 0.470 kg in the dynamic case. An increase 1 kWh of wind reduced carbon emissions by 0.391 kg, and the increase of 1 kWh of demand increased carbon emissions by 0.462 kg. The numbers differ between years, due to the changing composition of the GB power plant fleet and the relative prices of coal, gas and carbon.

As discussed earlier in the methodology chapter, half-hourly marginal emissions reductions of wind and solar may not reflect start-up and shutdown behaviour of power plants correctly. Accumulating the data set to daily averages alleviates this problem. The following table shows the marginal emissions for the regression with daily data.

 TABLE III.
 REGRESSION PARAMETERS OF THE DAILY MARGINAL

 CARBON EMISSIONS FOR THE BASE CASE AND THE DYNAMIC CASE

Daily marginal emissions factors in kg/kWh							
	All years	2012	2014	2016	2017		
Base case							
Solar β_S	-0.327	NA	-0.426	-0.396	-0.310		
Wind α_W	-0.494	-0.633	-0.563	-0.471	-0.423		
Demand γ_D	0.723	0.777	0.570	0.580	0.557		
Dynamic case							
Solar β_S	-0.300	NA	-0.426	-0.354	-0.261		
Wind α_W	-0.470	-0.640	-0.549	-0.448	-0.382		
Demand γ_D	0.725	0.780	0.575	0.586	0.548		

The emissions reductions are now on average 0.300 kg per kWh of solar and 0.470 kg per kWh of wind. Demand increases the carbon by 0.725 kg per kWh. The daily average values show that the emissions reductions are not only depending on the half-hourly changes in the energy system, but further start-up and shutdown emissions of fossil-fired generators must be accounted for adequately.

VI. CONCLUSION

The initial estimates suggest that the impact of wind and solar are reducing plant loading and thus affect efficiency. Using real data instead of simulations allows to quantify the impact of the part-loading and increases certainty. The preliminary results presented in this paper suggest that this effect reduce the carbon emissions reductions potential of wind and solar. The sums of carbon emissions between the base case and the dynamic case differ significantly.

Furthermore, we did observe significant differences in the carbon emissions reductions of wind by year, with a trend of decreasing numbers between 2012 and 2017. This is in line with the setup of the power system and its change away from coal to gas-fired power plants. Accounting for the efficiency loss caused by part-loading causes the CO₂ savings from wind to fall by 10.7 % and from solar by 0.2 % when using half-hourly data and averaged over all years. Using the daily regression and averaging over all years, the CO₂ emissions savings would decrease by 4.9 % for wind and by 8.3 % for solar.

VII. FURTHER WORK

The presented findings are of preliminary nature and require further development. One of the issues that can and should be captured more accurately, is the start-up and shutdown behaviour. This might have a significant impact in the carbon emissions reductions of wind and solar. This step is highly a challenging exercise in handling real life data with numerous sources of errors. The isolation of the start-up and shutdown emissions from other contributions allows us to identify the impact of each individual factor.

Additionally, the effect of choosing emissions factors for individual power plants needs to be clarified to isolate the effects of the dynamic case on the emissions reductions.

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