GridCarbon: A smartphone app to calculate the carbon intensity of the UK electricity grid

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GridCarbon is a smartphone app, first released in December 2009, that calculates the carbon intensity of the UK electricity grid. This paper reports on an update to the app, released in April 2017, that merges two online data sources in order to use actual and estimated wind and solar generation in the calculation of carbon intensity.

GridCarbon

GridCarbon was first released in December 2009 and uses instantaneous generation mix data from ELEXON, updated every five minutes, to calculate the carbon intensity of the UK electricity grid. Since its launch, renewable generation within the UK grid has grown steadily and now represents a significant proportion of electricity generation. Much of this generation is from wind and solar sources deployed within the distribution network and is un-metered. It is not included in the standard generation mix data. Thus, in this update of GridCarbon (version 1.6 on iOS and version 2.4 on Android), we combine estimates of wind and solar data with the instantaneous generation mix data to provide an improved estimate of the carbon intensity of the UK electricity grid.

Carbon Intensity

The updated version of GridCarbon makes use of two data sources, both available through the ELEXON portal[1]. The first is the *instantaneous generation mix* (FUELINST), categorised by fuel type, which provides 24 hour data divided into five minute periods, updated every five minutes.[2] The second is the *actual or estimated wind and solar power generation* (B1630) over the previous 48 hours, divided into 30 minute settlement periods, updated every 30 minutes.[3] This source provides estimates of wind and solar generation from both metered and un-metered sources, with much of the latter being small scale generation within the distribution network. Both data sets are also available on a public website.[4]

The carbon intensity of each unit of electricity generated is then simply found by weighting the carbon intensity, ci, of each individual generation source, i, by

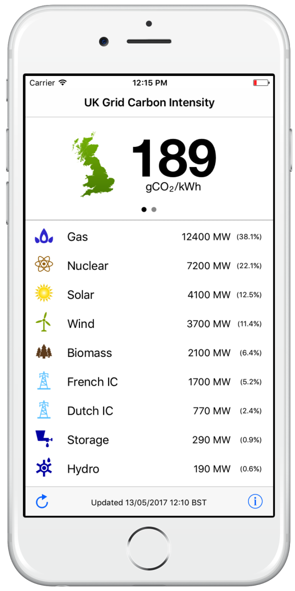

Figure 1: GridCarbon app showing live carbon intensity.

[1] `www.elexonportal.co.uk`

[2] `api.bmreports.com/BMRS/FUELINST/v1?APIKey=<APIKey> &ServiceType=xml`

[3] `api.bmreports.com/BMRS/B1630/v1?APIKey=<APIKey> &SettlementDate=<SettlementDate>&Period=<Period> &ServiceType=xml`

[4] `www.bmreports.com/bmrs/?q=generation/`

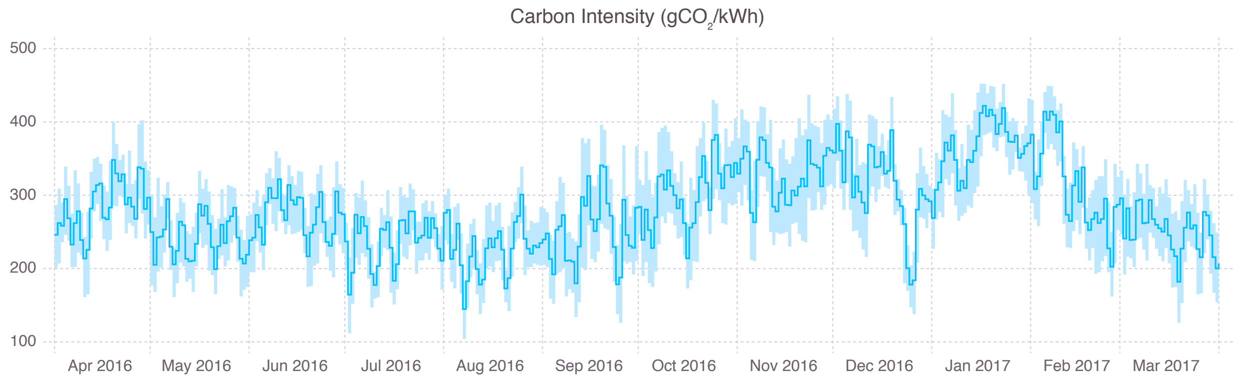

Figure 2: Daily minimum, average and maximum UK grid carbon intensity from 1st April 2016 to 31st March 2017.

how much its generation, g, contributes to the total:

$$CI_{\text{gen}} = \frac{\sum_{i=1}^{N} g_i \times ci_i}{\sum_{i=1}^{N} g_i} \tag{1}$$

Table 1 shows the carbon intensity of the sources used in both the previous versions of the app and in the updated version. The updated values are taken from Staffell, 2017.

Note that in earlier versions of the data API, biomass generation was categorised as 'other'. As of November 2017, biomass and other are included as separate categories. Note also that the electricity generated from pumped storage is assumed to be emission-free since the emissions are accounted for when the pumps consume electricity. The values of carbon intensity in the updated version of GridCarbon are on average 10-20 gCO_2/kWh higher than the previous versions due to the higher contribution of closed-cycle gas generation; this increase is offset somewhat by the addition of embedded wind and solar generation.

Since we wish to express the carbon intensity for each unit of electricity consumed, as opposed to each unit of electricity generated, we also include losses, l, in the transmission and distribution networks. Thus, the carbon intensity of consumption is thus given by:

$$CI_{\text{con}} = \frac{CI_{\text{gen}}}{1 - l} \tag{2}$$

Previous versions of GridCarbon used a value of 7% for these losses. The updated version uses a value of 8% representing an average value between 1996 and 2015 (Department for Business, Energy & Industrial Strategy, 2016). Figure 2 shows the daily minimum, average and maximum carbon intensity, calculated using this methodology, over the previous 12 months.

Missing Data

The two data sources used often exhibit periods of missing data. These are typically short; lasting less than one hour. In these instances we replace any missing data with the last available data. In addition, we find that the actual or estimated wind generation data often exhibits extended periods of missing data; sometimes lasting several days. Thus, we read wind data from both the instantaneous generation mix (FUELINST) and the actual or estimated wind generation (B1630) data feeds, and use the maximum of the two.

Predicting Wind and Solar

Finally we note that the actual or estimated wind and solar generation (B1630) data feed is typically delayed by 30 to 90 minutes compared to the instantaneous generation mix (FUELINST) data feed. To ensure that the app displays the most up to date data we make predictions of wind and solar generation over this short period. We display these predicted regions in the generation plot as highlighted bars at the extreme right of the generation mix bar graph (see Figure 3).

Table 1: *Carbon intensity of UK electricity sources.*

	Carbon Intensity gCO_2/kWh	
Source	Previous	Updated
Coal	910	937
Oil	610	935
Gas (Open Cycle)	480	651
Dutch Int.	550	474
Irish & East-West Int.	450	458
Gas (Closed Cycle)	360	394
Biomass	300	120
Other	300	300
French Int.	90	53
Hydro	0	0
Nuclear	0	0
Pumped Storage	0	0
Solar	0	0
Wind	0	0

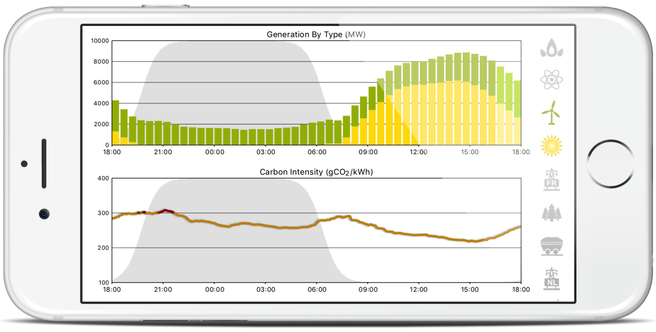

Figure 3: Highlighted bars (at extreme right of graph) indicating predicted wind and solar data.

Table 2: *Parameters for solar prediction derived from 2015 and 2016 solar generation data.*

Month	t_{sr}	t_{ss}	g_{max}
January	7.8	17.9	950
February	6.9	18.9	1750
March	5.6	20.0	2750
April	4.1	20.2	4100
May	3.7	21.5	4150
June	3.5	22.0	4300
July	3.6	21.6	4200
August	4.4	20.6	4200
September	5.0	19.6	3600
October	5.8	18.3	2800
November	6.7	17.1	1700
December	7.6	16.6	1250

Wind

To predict the wind generation we make use of the relationship between the value of metered wind generation within the instantaneous generation mix (FUELINST) data feed and that within the actual or estimated wind generation (B1630) data feed. In doing so we assume that metered wind generation is a constant factor of the total of metered wind and unmetered wind generation. We calculate this factor over the last four hours of the actual or estimated wind generation data, and then use the metered instantaneous generation mix (FUELINST) data, scaled by the reciprocal of this factor, over this short prediction period.

Solar

Predicting the solar generation is more complex as we have no parallel data feed, and solar generation can exhibit significant change over this short period. However, solar generation has a characteristic increase and decrease over the course of the day and we can use historic data to predict this behaviour.

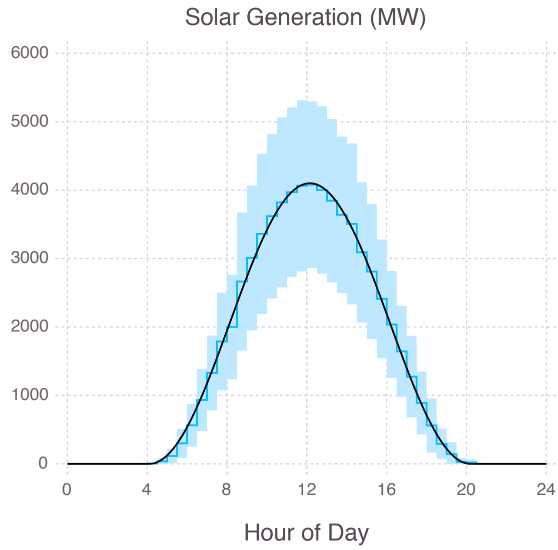

Figure 4: Comparion of predicated solar generation curve (dark blue solid line) and mean +/- standard deviation of 30 minute solar generation data (pale blue line and shading) for April 2015 and 2016.

To do so, we approximate the pattern of solar generation over the course of the day using a three parameter model consisting of a sunrise time, t_{sr}, a sunset time, t_{ss}, and a peak solar generation value, g_{max}. Our predicted solar generation, g_{solar}, is then assumed to be zero when the time, t is earlier than t_{sr} or later than t_{ss}, and given by:

$$g_{solar} = g_{max} \times \sin^2(\pi r) \tag{3}$$

otherwise, where r is given by:

$$r = \frac{t - t_{sr}}{t_{ss} - t_{sr}} \tag{4}$$

We find the values of t_{sr}, t_{ss} and g_{max} by fitting the resulting curve to monthly historic solar data from

2015 and 2016. The resulting values are shown in Table 2. Figure 4 shows an example comparison of this predicted curve with historic data for April.

While the value of $g_{\max}$ gives a good indication of the likely peak solar generation on any particular day, solar generation exhibits significant variation between days due to changing weather conditions. Thus, as with the prediction of wind generation, we calibrate this peak value using the the last hour of actual or estimated solar generation data available. This provides an effective and robust short-term prediction of solar generation over one to two hours.

References

Department for Business, Energy & Industrial Strategy (2016). "Government GHG Conversion Factors for Company Reporting: Methodology Paper for Emission Factors". In: URL: www.gov.uk/government/uploads/system/uploads/attachment_data/file/553488/2016_methodology_paper_Final_V01-00.pdf.

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