Why 100% renewable energy is not enough

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Introduction

Increasingly, private sector actors show a willingness to play their part in the fight against climate change. Large energy consumers set targets to green their energy supply and procure "100% renewable energy": the RE 100[1] initiative counts 51 member companies in the US, 77 in Europe, and over 160 in total. In the US, corporate buyers procured over 15 GW of renewables from 2013 to 2018[2], representing 10% of the total current installed US capacity for wind and solar (94 and 51 GW, respectively). In 2018 alone, 6.5 GW were procured through 75 transactions, leading to high growth expectations.

For those institutions motivated by decarbonization, such investments will require a rigorous, quantitative assessment of their carbon benefits. In contrast to today's dispatchable, fossil-fueled, thermal generation sources, the availability of solar and wind resources varies throughout the day and by location. In highly renewable power grids, the environmental quality of electricity will correspondingly also vary. Considering only annual or country-level carbon intensity data will lead to erroneous carbon accounting and ultimately inefficient investment. As is now recognized by some large corporate actors[3], claims of "100% renewable energy" do not guarantee commensurate emissions reductions.

Carbon accounting is challenging. Determining the impact on the environment from generating energy at a given power plant is a first hurdle. Electricity from one source cannot be distinguished from another, which makes the impact of consumption even more difficult to estimate. Finally, investment decisions made today will have impacts for decades to come.

Here we argue that despite these challenges, carbon accounting must move forward. Building the relevant set of metrics to monitor and account for emissions is critical. As more precise data become routinely available, they should be used to measure the carbon footprint of electricity consumption and production. Carbon accounting metrics aim to associate a certain environmental quality with the power flowing through the grid. It should become standard for such metrics to consider information on a local level and at a sub-daily time scale.

Solar-rich California is a case in point. Up to the early 2010s, investing in solar generation achieved high carbon emissions reductions in the middle of the day. Displaced energy and emissions were overwhelmingly from fossil-fueled generation. Early investors helped catalyze the nascent renewables industry. Today, investing in 100% electricity consumption from solar PV alone is not enough to compensate for night-time emissions, because the carbon intensity of the grid during the middle of the day is already much lower than that of fossil generation alone. Those institutions in solar-dominated grids that want to be at the forefront of the fight against climate change now need to catalyze a second tranche of investments that will target reducing these difficult nighttime emissions. This effect will only be visible if carbon accounting incorporates hourly measurements. As we show in our simple example, annual methods could overstate emissions reductions by 50% in a policy-compliant 2025 scenario, when solar energy reaches 25% of the annual mix.

In other locations, nighttime hours will be the cleanest, or there will be no difference between night and day. Location-specific assessments are needed. Wherever variable wind and solar generation are high, hourly carbon accounting will be required to make those assessments and guide investments.

Different tools to measure the impacts of our energy choices

Different carbon accounting metrics are available to consumers for choosing when and where to consume the energy they need. Carbon intensities, or Average Emissions Factors (AEFs), measure the environmental quality of power flowing through the grid at a given place and time, as the ratio of emissions to electrical energy, in units of $kgCO_2eq$ per MWhe. One option to construct them is to weight estimates for the carbon intensity of each generation source by electricity produced. Table 1 provides the median of a compilation of emissions intensity estimates[4]. Generating electricity by burning coal has twice the emissions of burning gas, which has itself ten times more than by using current solar generation technologies.

Marginal Emissions Factors (MEFs) measure the change in emissions with respect to changes in electricity, also in units of $kgCO_2eq$ per MWhe. MEFs are a useful tool alongside AEFs in that they correspond to the emissions intensity of the marginal generator or consumer in the system. While AEFs can be used to measure carbon footprints, MEFs are a direct measure of the response of the power system to a change in consumption or generation. MEFs can be computed to estimate environmental impact both in the short[5,6] and in the long[7] run.

Constructing a relevant accounting metric depends both on the availability of data and the target question. In much the same way as for country-level emissions accounting[8], it is possible to (i) focus on the CO_2 being emitted (production-based accounting), or (ii) on the CO_2 to be associated with the consumption of electricity (consumption-based accounting). Choosing the right granularity in space and time is also key. The appropriate resolution is typically one that captures statistically significant variations but excludes higher resolution noise. For power systems with high shares of wind and solar, the appropriate temporal resolution will capture daily availability patterns, and is likely to be less than a few hours[9]. The appropriate spatial resolution will typically be one for which it is possible to fully account for production, consumption, imports and exports so that consumption- and production-related emissions can be computed.

For consumers taking a more active part in sourcing the energy they consume, estimating their net carbon footprint can be more complex. If they choose to decarbonize their energy supply by directly investing in renewable energy generation assets, we must now estimate the carbon benefits they are providing by producing clean energy. Different options to compute carbon credits are currently under experimentation, e.g. in California's cap-and-trade program, or in the European Union's Emissions Trading Scheme. In our example, we will use a generic offset calculation by which supply- and generation-side assets are accounted for independently.

Case study: decarbonizing the electricity procurements of a 1 MW constant load in California

As an illustrative example of carbon accounting in a power system with high solar generation, we now consider the example of a 1 MW constant load in the California Independent System Operator (CAISO) service territory, the grid mix for which is reported in Table 1. We quantitatively evaluate four decarbonization strategies: the consumer purchases enough renewable generation to cover 100% of annual consumption from 1) solar only; 2) wind only; 3) half wind and half solar; and 4) the consumer owns no generation. To achieve a 100% renewable energy supply, a 1 MW constant load consumer would need to purchase either 3.16 MW of wind or 3.60 MW of solar generation capacity.

In this example, we use both AEFs and MEFs for the CAISO grid. The consumer's net environmental impact is computed as the difference between the carbon released by purchasing grid electricity and the carbon avoided by purchasing renewable power. We assume that the carbon intensity of grid electricity corresponds to the AEF, and that the procurement of renewable generation displaces the marginal producing units, whose carbon intensity corresponds to the MEF.

Publicly available hourly grid mix data for the CAISO service territory are used to (i) compute wind and solar generation data for the assets purchased by the consumer; and (ii) compute hourly AEFs and MEFs for the CAISO territory[10]. AEFs are estimated from hourly generation mix data weighted by the corresponding carbon intensities in Table 1. MEFs are estimated from hourly regressions of stepwise changes in carbon emissions and generation as in previous work[5,6]. In the 2025 scenario, solar generation capacity has increased threefold from 2016 and solar is considered the marginal source when no more dispatchable thermal generation can be displaced and the solar must either be curtailed or stored. Figure 1 shows average daily profiles for CAISO AEFs and MEFs and highlights increasing intra-day variability as more solar PV is added to the system.

The first two columns in Figure 2 show average daily profiles for the net carbon footprint of the consumer in 2018 and 2025 and underscore the weight that nighttime emissions will likely play in the carbon impacts of the future CAISO power grid. The bar charts in the third column of Figure 2 compare the use of hourly and yearly data to compute the consumer-purchaser's attributable emissions reductions. Using both hourly and yearly data, the carbon footprint of consumption decreases as the average grid power is decarbonized. Credits from purchasing renewables vary depending on the emissions rate of the marginal generator, which is currently dominantly gas-powered, but will be dominantly solar-powered at midday in 2025. In California, the emissions rate of the marginal generator is higher than the average grid emissions rate, so purchasing renewables to meet 100% of consumption results in a negative net carbon footprint.

Using hourly data, the 2018 emissions attributable to the consumer would be reduced by 150% from purchasing wind and 137% from solar. In 2025, reductions would be 135% for wind, but drop to 66% for solar: in an already solar-rich future California grid, adding nighttime wind power has more environmental value than adding daytime solar power.

Using yearly (averaged) data, intra-day fluctuations cannot be captured and the time at which renewable power is delivered does not matter: 2025 emissions reductions are 131% for wind and 119% for solar. The difference between wind and solar is only related to the difference in their carbon intensity. In this simple example, using yearly data overestimated reductions from purchasing solar by over 50%.

Annual accounting is valid when intra-day fluctuations are small and when energy demand can always absorb additional renewable energy generation, irrespective of the time of day. Although those assumptions may be valid for low penetrations of renewable generation, it is not true when renewable generation increases to the level that the California power grid is already experiencing, unless all the excess renewable generation is stored for later consumption. In March and October of 2018, curtailments of solar and wind reached 3% of generated energy[10].

This case study provides an illustrative example of a power grid where renewable generation (solar) will be more readily available during the day than at night. In other locations, the opposite may be true: for comparison, Figure 1b shows daily profiles for AEFs and MEFs in Great Britain from 2015 through 2018, where the nighttime hours are the cleanest[10].

In this case study, the environmental impact of different renewable power procurement options was assessed in three different years. Another action available to the consumer is to change consumption patterns to better match clean power availability. To assess the impact of changes in consumption and production over multiple years, long-run consumption- and production-based MEFs can be used[7].

Conclusion

As the fraction of renewable energy in the power grid increases, institutional targets to procure "100% renewable energy" should use hourly accounting to accurately measure the carbon emissions reductions achieved and can result in either less or more than 100% emissions reductions. In solar dominated grids such as in California, hourly accounting reveals that adding new wind capacity has much greater carbon benefit than adding new solar generation. Location specific assessments will be needed to make similar assessments for other regions, where other generation sources may hold greater environmental value. Research to inform such assessments and design transparent, precise and meaningful carbon accounting will be of great help.

A rise in the penetration of renewable generation changes marginal emissions factors. This parallels the well-studied merit-order effect[11] or price-suppression effect by which the correlated output of renewables shifts the supply curve to the right and reduces marginal clearing prices, depressing the revenues earned by renewables; but only appears when hourly data are considered.

Looking to the future, achieving concomitant emissions reductions with renewable generation will also require shifting loads to take advantage of low carbon generation sources by utilizing energy storage and scheduling those loads that are flexible to better follow the availability patterns of renewables[12].

As power grids accommodate increasing shares of renewable generation with daily fluctuations in availability, both the carbon footprint of a large consumer and the environmental value of renewable energy assets are dependent on the grid mix they interact with. To capture these effects, carbon metrics must shift from using yearly or even monthly averages to hourly data. Only then will they convey accurate control signals to induce both appropriate investments in low-carbon generation assets and load-following behavior, especially when a price is put on carbon[13].

Data availability

All data used in this commentary are publicly available[10].

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Figures and Tables

Table 1 | 50th percentile from a range of studies for life-cycle carbon intensity of electricity generated from each source according to Table A.II.4 in the IPCC 2011 Special Report on Renewable Energy Sources and Climate Change Mitigation[4], as well as power grid mix for the California ISO in 2016, 2018 and 2025 (including imports) and Great Britain in 2015 and 2018 (excluding imports, that typically represent around 5%)[10]. The rows that exhibit the largest changes across years in California are highlighted (solar PV, thermal and imports). The policy-compliant 2025 scenario for California is generated by increasing solar generation capacity by a factor of three and assuming displaced generation sources are thermal and imports.

Fuel	IPCC Carbon intensity (kgCO2-eq/MWhe)	Fraction of total energy produced (%), CAISO balancing area			Fraction of total energy produced (%), GB	
		2016	**2018**	**2025E**	**2015**	**2018**
Biogas	230	0.7	0.9	0.7	0.00	0.00
Biomass	230	0.8	1.3	0.8	0.00	6.05
Geothermal	42	3.7	3.6	3.7	0.00	0.00
Hydro	4	9.8	9.9	9.8	2.50	2.16
Nuclear	16	8.2	8.2	8.2	23.87	22.78
Small Hydro	4	1.3	1.5	1.3	0.00	0.00
Solar PV	**46**	**8.4**	**11.7**	**25.3**	2.82	4.21
Solar thermal	22	0.6	0.5	0.6	0.00	0.00
Gas	**469**	**32.7**	**27.9**	**21.2**	30.84	43.32
Wind	12	6.0	7.1	6.0	12.00	15.70
Coal	1001	0	0	0	27.96	5.78
CAISO Imports	**428**	**27.9**	**27.6**	**22.5**	NA	NA

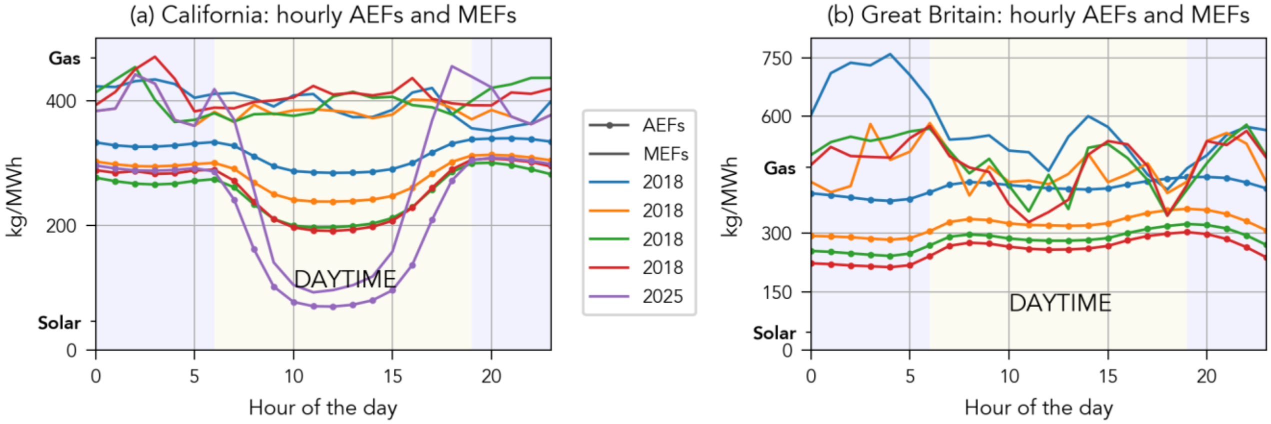

Figure 1 | Average hourly profiles for the marginal (MEFs) and average (AEFs) emissions factors in (a) California (CA) and (b) Great Britain (GB)[10]. AEFs are estimated from hourly generation mix data weighted by the corresponding carbon intensities in Table 1. MEFs are estimated from hourly regressions of stepwise changes in carbon emissions (also computed from Table 1) on stepwise changes in generation for dispatchable generation sources. In the 2025 scenario, solar generation capacity has increased threefold from 2016 and solar is considered the marginal source when no more dispatchable thermal generation can be displaced and the solar must either be curtailed or stored. While the carbon intensity of the CA grid is expected to continue to decrease during the daytime (6 AM to 7 PM), the quality of nighttime power is not expected to change significantly. This will lead to strong intra-day variations in the environmental quality of electricity. In April of 2018, electricity was twice cleaner in the middle of the day as in the middle of the night. In GB, coal generation decreased from 40% of the GB generation mix in January of 2015 to 20% a year later (and is mostly active in the winter months).

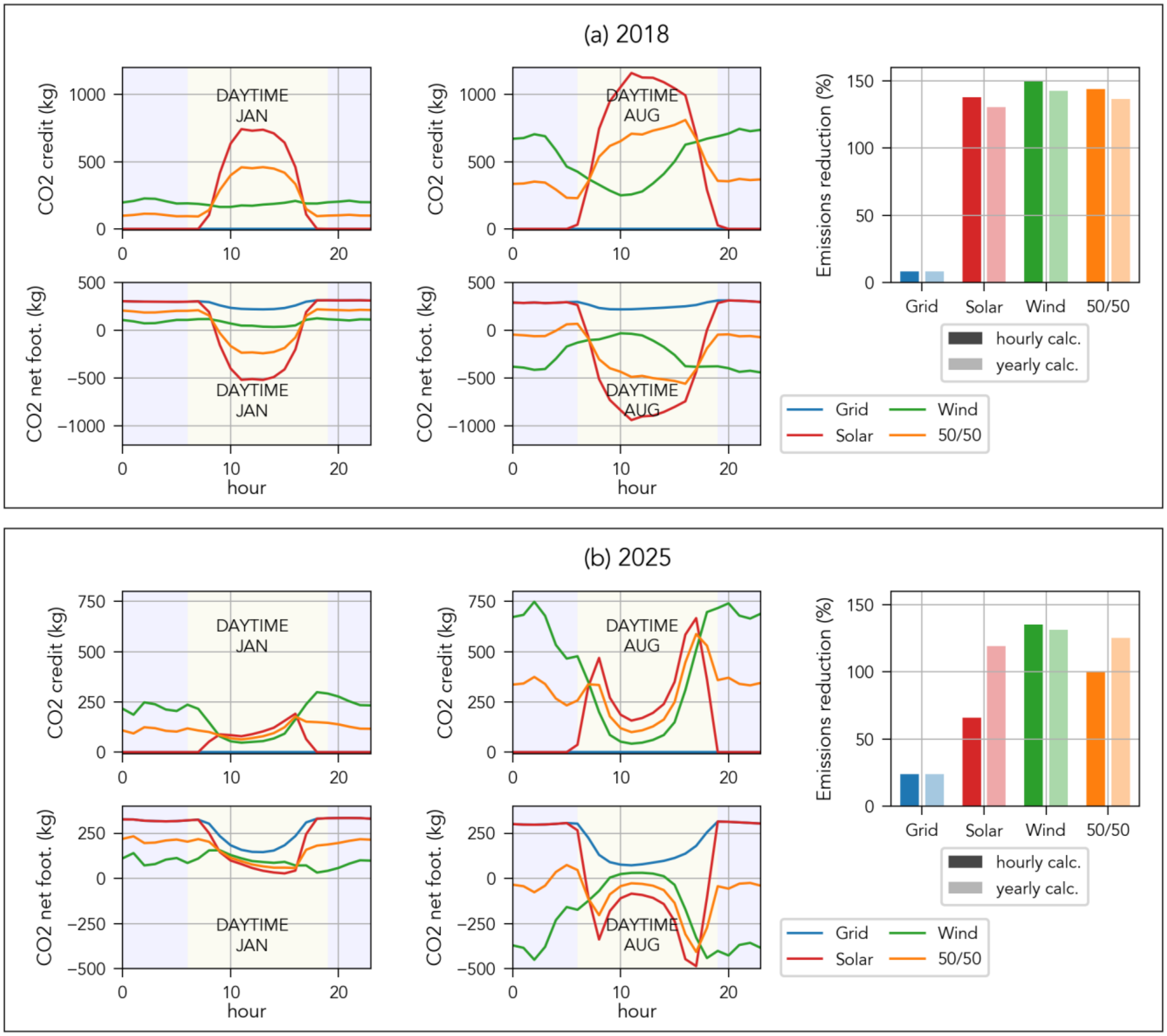

Figure 2 | (a) 2018 average hourly carbon credits and footprint in January and August, and annual emissions reductions from 2016 levels comparing the use of hourly and yearly methods for carbon accounting[10]. Calculations are for a 1 MW constant load under different 100% renewable energy procurement options. Hourly carbon credits are earned as the pollution avoided by renewable energy replacing the marginal generation source (computed using MEFs). Hourly carbon footprints are computed as the difference between pollution from consuming average grid electricity (computed using AEFs) and the hourly carbon credits. In the different scenarios, enough renewable energy capacity is purchased to meet 100% of consumption on an annual basis (3.60 MW for 100% solar and 3.16 MW for 100% wind). Since we are assuming a 1 MW constant load, hourly and yearly carbon footprints under the 100% Grid options are the same, but this will not be the case in general for a non-constant load. (b) Similar data for the 2025 scenario. In a solar-dominated CAISO grid, the benefit of purchasing additional solar generation is limited. Purchasing wind generation retains environmental value to decarbonize nighttime power.