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Recent results from energy and emissions tracking in the US electricity system

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Abstract—Electric sector emissions represent a large and growing fraction of anthropogenic emissions and should be a strong focus for environmental policy measures. In electric grids with significant penetrations of renewables, the emissions intensity of electricity varies in space and time. To encourage and guide decarbonization efforts, we need better tools to monitor the emissions embodied in electricity consumption, production and exchanges. Previous efforts resulted in a dataset for 2016 electricity and emissions at the hourly and balancing-area levels in the US electricity system. We now provide tools to make such datasets available much faster, by using an approximation for released emissions and an algorithm to automate data cleaning. As an example of how this type of new, detailed information on the electricity system can be used, we assess the current impacts of high penetrations of renewables on other grid components in the US. We demonstrate how dispatchable generation and electricity exchanges play an essential role in integrating fluctuating wind and solar generation.

Keywords—carbon intensity of electricity, renewable energy policy, electricity system emissions factors

I. INTRODUCTION

As efforts to curb greenhouse gas emissions intensify, monitoring decarbonization progress and tracking the impacts of different policy actions in a timely manner will be critical to achieve climate goals. New tools are needed to measure and analyze emissions from different sectors of our economies at increased granularity in space and in time.

The electric sector should be a prime target for these efforts, since it represents a large and growing share of man-made emissions. Emissions from electricity and heat generation represented 41% of the world’s 32.8 Gt of carbon dioxide (CO2) emissions from fuel combustion in 2017 [1]. CO2 emissions from fuel combustion can be expected to represent 58-69% of the world’s total greenhouse gas (GHG) emissions (including land use; data from [2] using 100-year Global Warming Potential for methane and nitrous oxide). In the United States (US), electricity represented 28% of GHG emissions in 2016 [3].

Large-scale deployment of low-carbon and renewable electricity is increasingly advocated as an effective decarbonization pathway for electricity systems. The variability of wind and solar electric power is a concern when they represent large fractions of the generation mix and is now better understood [4]. The integration costs for wind and solar will ultimately depend on how well conventional generators can adapt their operational strategies and respond to fluctuations in renewable output.

The decarbonization benefits provided by renewable generation should be assessed by analyzing their impact on released emissions. A common tool to analyze emissions in the electric sector is the emissions factor (EF), that quantifies the mass of CO2 that is released to the atmosphere per unit electrical energy. By this metric, coal is roughly twice dirtier than gas, which is ten times dirtier than other generation technologies (using life-cycle analysis estimates) [5]. From 2001 to 2017, the carbon intensity of the United States (US) electricity system decreased by 30% [6] (using direct emissions estimates) as gas and renewables displaced coal in the generation mix.

A growing body of work is concerned with understanding how EFs vary by location, season or time of day [7, 8]. To better capture the impact of environmental measures, the use of marginal EFs has been advocated as a tool to measure the impact of short [9, 10] or long-term [11] policy decisions. EFs can use production or consumption of electricity as the accounting basis [12-14]; but linking changes in production and consumption at different locations of electricity grids, effectively large interconnected machines, is difficult.

Previous work by the same authors developed a methodology to compute hourly consumption- and production-based emissions in the US electricity system [15] and applied it to 2016 data for the sixty-six continental Balancing Authorities (BAs) in the US. This work combined data from three publicly available sources on electricity and emissions using a fully coupled economic multi-regional input-output (MRIO) model of the electricity system, adapting previous work to quantify the emissions embodied in the trade of goods and services between countries [16, 17].

In this framework, pollution is embodied in generated electricity and subsequently flows through the electricity network. Produced emissions are defined by the administrative territory in which they are physically emitted. Consumption-based emissions are defined by the administrative territory in which electricity is consumed, and we refer to them as “consumed” emissions. We similarly refer to “traded” emissions as the emissions embodied in hourly electricity exchanges.

In this work, we now provide the tools to perform similar analyses in near real-time and to continuously monitor emissions rates in the US electricity system, which is responsible for close to a third of the carbon dioxide that is released to the atmosphere each year in the US. Emissions estimates from this work rely on electric system operating data, publicly available with a time lag of hours to days, and technology-specific emissions factors.

This work uses a methodology to automatically reconcile inconsistent data on electricity generation, consumption and exchanges. We also depart from [15] in the data source that is used to compute produced emissions (arguably less precise, but available in real-time as opposed to quarterly). The raw and cleaned electricity data as well as the consumption- and production-based emissions from this work will be streamed to a publicly available data collection service.

II. Data and Methods

In this work, we leverage publicly available data from the US Energy Information Administration (EIA) [19]. This dataset provides electric system operating data on generation, consumption and exchanges of electricity for every hour and at the level of the balancing area (BA). We argue that tracking emissions at the BA level is natural because they correspond to the physical organization of the electricity system, where control-room operators must continually monitor the state of the electric grid to ensure that supply can meet demand and line flows remain technically acceptable. In the remainder of this paper, BAs will be referred to as "regions" to simplify language. A full table of abbreviations for the different regions in the US can be found in the Supplemental Information document of [15].

Since July of 2018, the EIA online data facility also releases the hourly generation mix in each region, which allows us to estimate hourly emissions released by using technology-specific emissions factors. Specifically, if we call f_s the emissions factor for generation source s and $P_{r,s}$ the output from generation source s in region r, we compute the emissions produced in region r as:

$$F_r = \sum_{s \in S_r} f_s P_{r,s}\,, \qquad r \in R \qquad (1)$$

For the results presented in this paper, we use the most recently available life-cycle analysis estimates from the IPCC [5] as the technology-specific emissions factors. In contrast, our previous work [15] used power-plant-level measurements of emissions to estimate hourly emissions, available from the US Environmental Protection Agency's (EPA) Continuous Emissions Monitoring Systems (CEMS) [20]. Although they provide invaluable information on the operation of US electricity generation units, the CEMS data are only released once every quarter. Additionally, not all power plants report to this database. In the California Independent System Operator (CISO) for instance, we found that 30% of the 2016 emissions – mostly those corresponding to Combined Heat and Power (CHP) plants – were not reported. To infer missing emissions, our previous work used a more complete bi-annual emissions inventory by the US EPA [21] as well as a significant amount of manual data cleaning.

Directly using the EIA electric system operating data can also be challenging. As confirmed by the EIA documentation [19], there are numerous inconsistencies in the data (*e.g.* interchange reported by region r_1 to or from region r_2 does not match the corresponding report by region r_2). We have found these inconsistencies are particularly problematic when computing consumption-based emissions because the MRIO framework relies on solving linear systems. When the data supplied to our solver is inconsistent, the linear system is often ill-conditioned and solving it is prone to numerical instability.

In our previous work [15], significant efforts were devoted to manual data cleaning to avoid issues for both the electricity and emissions data sources. In the context of this work, data cleaning procedures were fully automated so that the electricity and emissions dataset we release can be updated on an hourly basis. Our methodology relies on solving on optimization program to compute minimal adjustments to the data such that they are physically consistent and will be developed in more detail in the full version of this paper. Although these methods were developed with our emissions tracking application in mind, we believe they will benefit other consumers of electric system operating data as well, *e.g.* for researchers attempting to create realistic simulations of electricity systems in the context of capacity expansion modeling.

We follow the same procedure as in [15] to compute consumption-based emissions. Following the EIA API's convention, $ID_{r1,r2}$ corresponds to the electricity sent from r_1 to r_2, is negative for imports and positive for exports. Imports from r_1 into r_2 are $u_{r1,r2} = -min\,(-ID_{r1,r2}, 0)$ and we write the following linear system to compute the consumption-based emissions factor in region r, x_r:

$$x_r(G_r + U_r) - \sum_{r_2} x_{r_2} u_{r,r_2} = F_r, \qquad r \in R \qquad (2)$$

G_r corresponds to total generation and U_r to the total imports for region r, $U_r = \Sigma_{r2}\, u_{r,r2}$. This equation corresponds to equation (4) from [15] and provides valuable information on how embodied carbon emissions propagate through the electric grid, from production to consumption. We note that (2) accounts for transshipments of electricity and emissions across regions and that the MRIO system we consider is fully coupled.

III. Results

A. Continuously monitoring electricity and emissions

In Fig 1., we show maps for the embodied carbon consumed and exchanged by the different regions in the US electricity system, that compare average hourly daytime and nighttime behavior in the spring of 2019. The western interconnect consumed 13% less carbon during daytime than during nighttime in the spring of 2019, while the eastern interconnect consumed 31% more. Nighttime wind power lowers the nighttime carbon intensity of Texas (ERCO) and the Southwest Power Pool (SWPP), while daytime solar lowers the daytime carbon intensity of the California regions. Abundant hydroelectric resources are behind the clean power that is produced and exported from the northwest of the US system. Exchanges play a crucial role in the western interconnection, while they play a much weaker role in the eastern US grid.

The carbon intensity of consumed electricity varies in time as well as in space, as highlighted by Fig. 2, where we show profiles for the median electricity generation from the dominating renewable energy resource for a region and the corresponding profile for the median consumption-based carbon intensity, for different time aggregations. Availability patterns for hydroelectric power are typically seasonal, as can be seen in the Bonneville Power Administration Territory (BPAT), where hydroelectric production typically peaks in the spring. Solar generation displays strong daily patterns, as can be seen in the California Independent System Operator (CISO) data. The effect is strongest in the spring, when solar generation is already high and electricity demand is not as high as in the summer. In the ERCO, wind generation is typically stronger in the nighttime. The

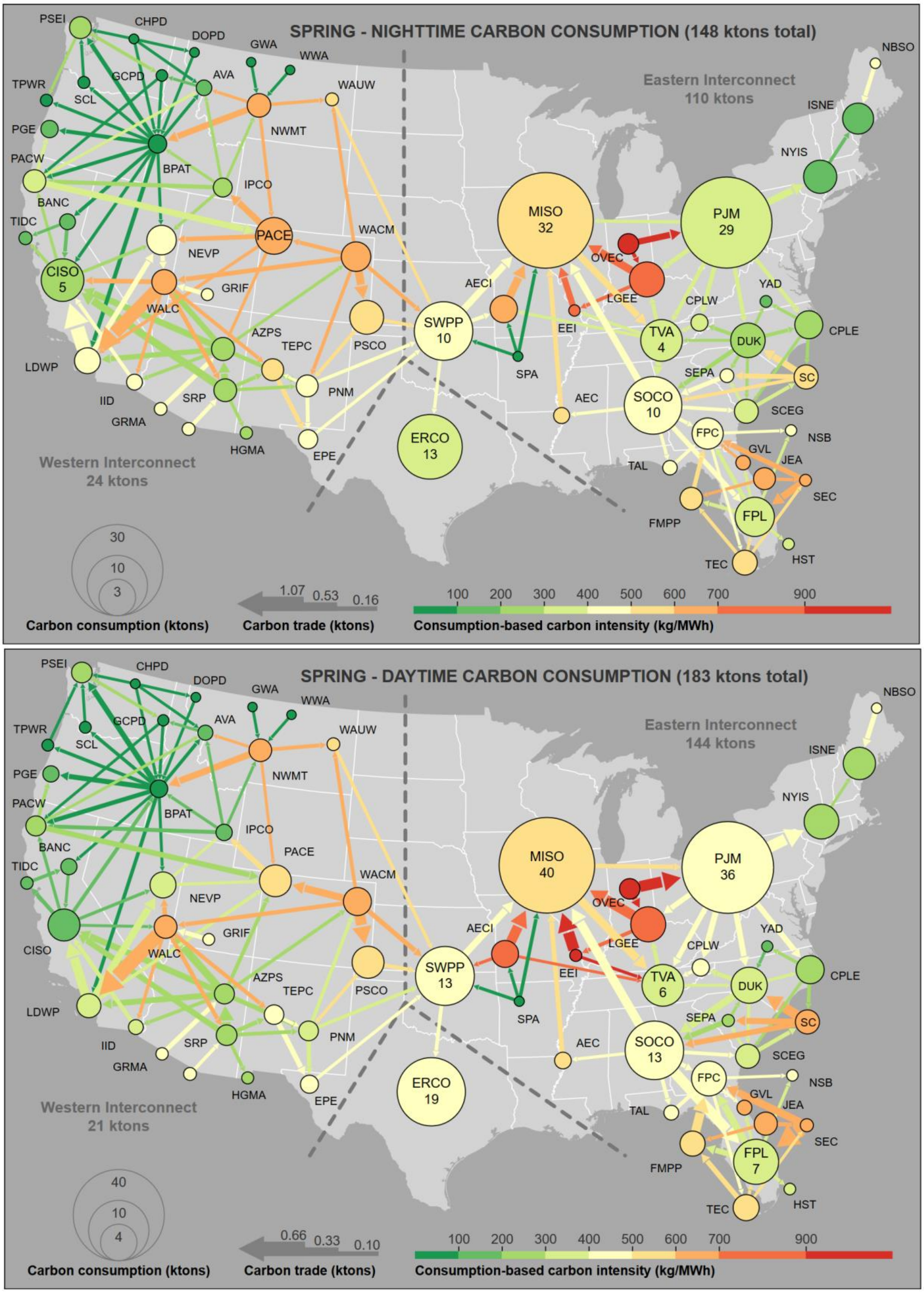
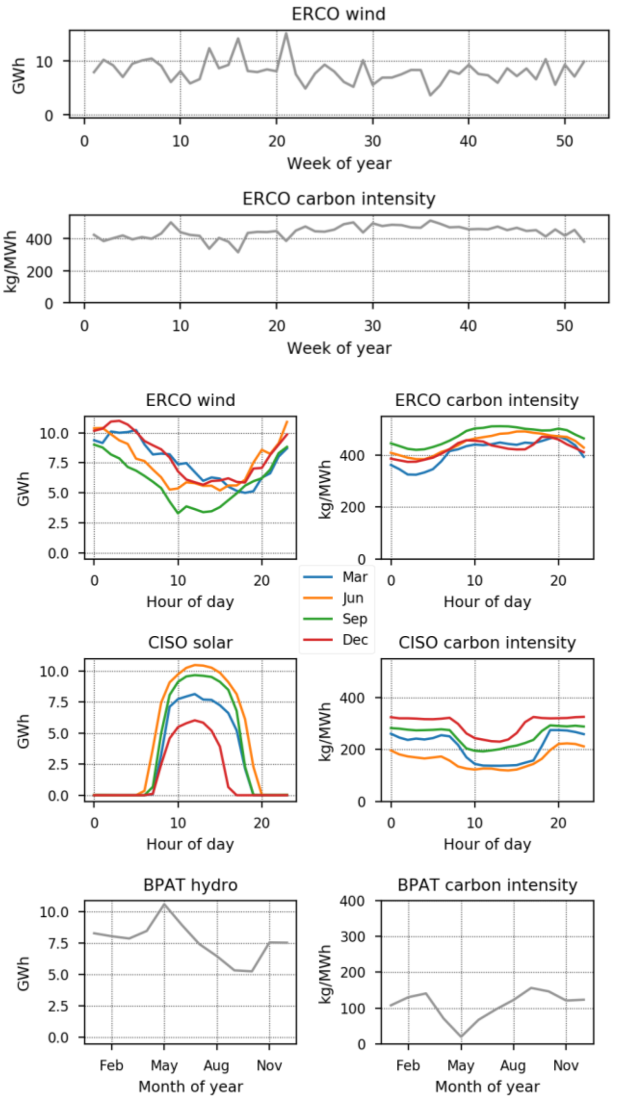


Fig. 1. Average carbon consumed and exchanged by the different regions in the US electricity system in the spring of 2019. Nighttime is defined as 11pm-5am EST or 8pm-2am PST. Daytime is defined as 12pm-6pm EST or 9am-3pm PST.

Fig. 2. In highly renewable grids, the carbon intensity of electricity consumed varies in time. Median hourly renewable generation and median hourly consumption-based carbon intensity for three regions.



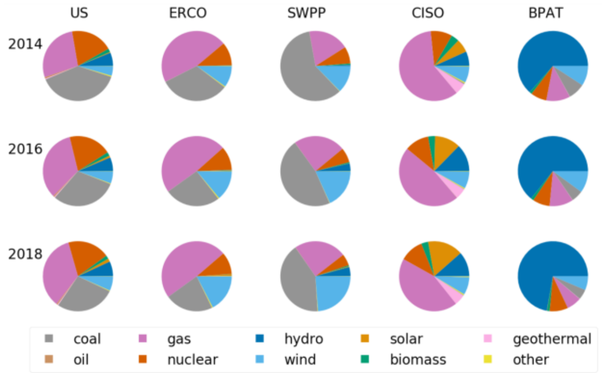
availability of wind generation can also vary tremendously from week to week.

These variations in electricity system carbon intensity are the direct result of increasing penetrations of renewables and can be expected to grow as efforts to decarbonize electricity generation continue. As we will show in section III. C., however, other generation assets must now routinely ramp production up and down to accommodate fluctuations in renewable output, particularly from solar and wind, providing a supporting role that will be difficult to replace.

B. *Renewables and gas continue gaining ground on coal*

Because of the large additions in renewable generation capacity in the past few years, the share of electricity generation has been steadily growing, as shown in Fig. 3, where data is provided from 2014 to 2018. Overall in the US system, the weight of coal dropped from 39% to 28% during that time interval. This was mostly to the benefit of gas-fired generators (28% to 35%), whose carbon emissions per unit power produced are roughly half those of coal plants. The growth in renewable generation is mostly attributable to wind (4.4% to 6.5%) and a lesser extent solar (0.4% to

Fig. 3. Renewables on the rise. Generation mixes for selected regions in the US (data from eGRID [21]).



1.5%), while the shares of hydroelectric and nuclear remained stable. Wind generation grew fastest in the ERCO and in the SWPP, from 10% to 17% and 13% to 24%, respectively. In both regions, this was at the expense of coal. In the CISO, solar now accounts for 16% of local generation (but only 12% of served electricity demand; the CISO imports a third of its electricity annually).

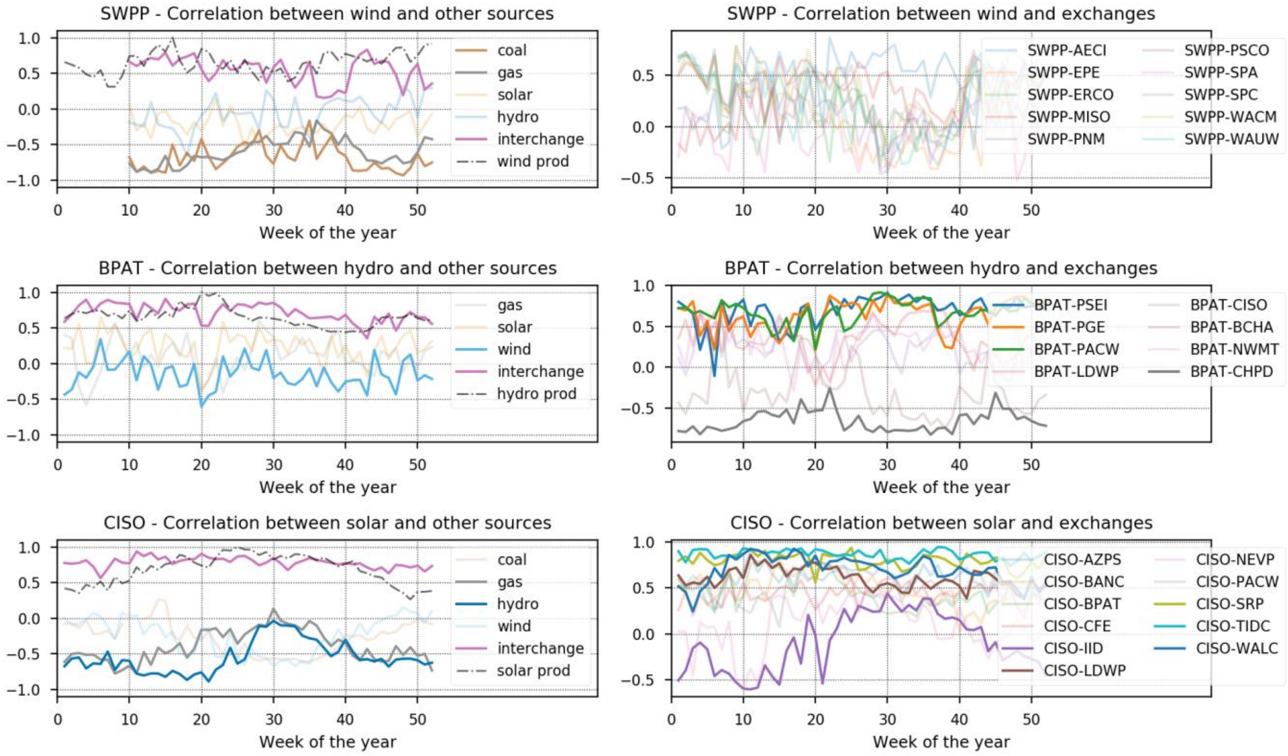
C. *Making way for renewables: the integration challenge*

To evaluate how large-scale renewable generation currently impacts other generating units in the US electricity system, we compute the weekly correlation between the generation from the dominating renewable resource and other grid mix components (including interchange) for three different regions, using hourly data from July 2018 to the present. Summary results from this analysis are shown in Fig. 4. In the left column, we also plot the weekly mean generation for the dominating renewable resource (in dashed black, normalized by the maximum).

In the Southwest Power Pool (SWPP), wind generation represented 25% of the generation mix and weekly averaged hourly wind generation peaked at 11.8 GW in April. Coal (34%) and natural gas (24%) were the two other major sources of electricity, while net exports were a much smaller fraction of generation (1%). In the Bonneville Power Administration Territory (BPAT), hydroelectricity represented 65% of the generation mix, and the weekly average of hourly hydroelectric generation peaked at 11.7 GW in April, roughly double the average September output. BPAT also had significant wind generation (8%) and was a net exporter of a large fraction of the power it produced (58%). BPAT is particularly interesting in that it simultaneously imports and exports significant amounts of power (exports were 86% of total generation while imports were 28%). In the CISO, solar generation represented 16% of the generation mix and the weekly average of hourly solar generation peaked at 4.5 GW in June (if we restrict data to the middle of the day, weekly averaged hourly generation peaked at 10.4 GW). Winter solar generation was roughly half of the summer output. The CISO imports a large fraction of the power it produces (25% of demand). Note that interchange is treated the same for all three regions and is positive for exports and negative for imports.

Nuclear generation is mostly run as a baseload resource in the US electricity system and is therefore uncorrelated with fluctuations in renewable generation sources, which is why nuclear is not considered in Fig. 4.

Fig. 4. Weekly averages for hourly correlation between the dominating renewable resource and other generation sources (left) and selected interchange routes (right), for three regions in the US electricity system. In the SWPP, data before for the first ten weeks is not trusted.



In the SWPP, wind generation drives higher exports. Coal and gas generation is scheduled to accommodate fluctuations in wind power generation and they are negatively correlated. Wind also displays strong negative correlation with coal and gas in the ERCO. The same is not true for exports, that are much smaller in the ERCO. In the MISO, similar negative correlations can also be found, but the effect is less pronounced, which is probably because wind represents a much smaller fraction of the generation mix.

In the BPAT, hydroelectric generation displays strong positive correlations with exports, and to a lesser extent, is negatively correlated with wind generation. A possible interpretation for this is that some hydroelectric generation is run to accommodate the fluctuations in wind generation, but the rest is run independently. This is supported by normalizing quantities by total hourly generation: the negative correlation between fractions of wind and fractions of hydro becomes much stronger.

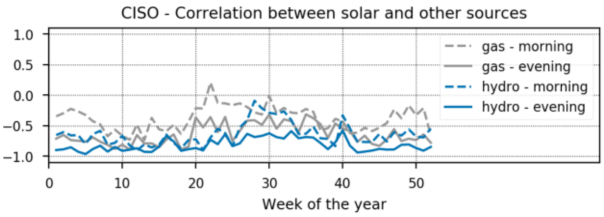
In the CISO, increased solar generation drives higher exports (or equivalently, fewer imports). Similarly, natural gas and hydroelectric resources are also scheduled to support solar by reacting to fluctuations and therefore display strong negative hourly correlations with solar generation for most weeks of the year. However, in summer, gas and hydro perhaps surprisingly lose most of their correlation with solar. One possible explanation for this is that the summer is also a period when wind generation is stronger during the nighttime, which reduces the integration burden for gas and hydro in those months. This can be seen in the negative correlations between solar and wind in summer. A second, less immediate explanation stems from the fact that daytime demand is much stronger in California in summer, driven by high temperatures. The weekly correlations between the same quantities normalized by demand is also weaker in summer than in winter, but the seasonal effect isn't as strong as for the unnormalized generation values. This can be explained by the different effects that are at play in the morning and in the evening. In the summer, during the morning solar ramp, gas and hydro generation must also increase to accommodate high demand. The output from all three generation sources is positively correlated. Relative to demand, however, solar increases while gas and hydro decrease. When the sun sets on the other hand, demand typically stays strong, and gas and hydro facilities must greatly increase their output to match the sudden decrease in solar generation. Fig. 5 highlights these morning and evening effects.

In the second column of Fig 4., we show the weekly correlation between generation from the dominating renewable resource and specific electricity exchange routes. We highlight those lines that have average absolute correlations above 60%. Four of the CISO connections are strongly correlated with solar generation. In the spring and winter, the connection with the Imperial Irrigation District (IID) is negatively correlated with solar, which can be explained by IID's strong solar generation. The same is true for the connection between the BPAT and Chelan County PUD (CHPD), that generates significant amounts from hydroelectricity. Interestingly, none of the SWPP connections seem to play a buffer role for wind, although the aggregate formed by the connections clearly does.

IV. Discussion

The US electricity system is slowly decarbonizing. Although much of the progress of the recent decade is attributable to gas-fired generators replacing traditional coal-fired US power plants, renewables have also steadily been

Fig. 5. Morning and evening correlation of solar with gas and hydro in the CISO.



gaining ground. Our results show how the carbon intensity of consumed electricity varies in time and in space in electric grids with significant penetrations of renewable generation. Continuously tracking embodied emissions flows will be critical to monitor decarbonization progress and direct climate policy to when, and where, it is most useful.

Large-scale renewables are now an integral part of daily operations throughout the US power grid. Precise characterizations of the stress that renewable generation places on conventional generators at different levels of renewable penetration are needed. Our results show that other generation units, most often gas- or coal-fired, respond to fluctuations from renewables and play an essential role that will be difficult to replace. Different effects drive the operating schedules of generators. Untangling those effects can be complex. Electricity exchanges are also play found to play a key role in renewables integration.

As installed capacity for renewables grows, it is likely electricity exchanges will too. Tracking tools like those that we provide to monitor electricity and carbon flows will become increasingly useful to decision makers designing environmental policy measures.

Performing in depth analyses and characterizations of the way the different electricity grids are adapting their operations to renewables will also be critical to push the decarbonization frontier. Such analyses will provide valuable insights to grids that are exploring decarbonization pathways or have not yet committed to a climate strategy, as well as to regions of the world where electricity grids have yet to be built.

Although arguably less precise than the method that was used in our previous work [15], the method we used in this paper allows us to provide estimates much faster than was previously possible. Additionally, it would not be difficult to refine the calculation using more precise historical data, *e.g.* by using region-level technology-specific emissions factors – these could be updated on a quarterly basis using data from the US EPA's CEMS [20], one of the three data sources that was used in [15]. The automated data cleaning procedure that we designed could also be improved, for instance by using a dynamic model of the US electricity system together with signal processing techniques such as Kalman filtering.

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