On the Complementary Variability of Wind and Solar Power

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Summary

The variability of and correlations between large-scale, distributed wind and PV generation across a northern US state is evaluated and contrasted. We analyze three years of hourly-interval, time-synchronous data from the State's wind fleet and distributed PV production simulated with SolarAnywhereTM. Despite a significantly higher capacity factor (wind: 37% vs. solar: 16%), distributed wind exhibits more variability than solar at timescales longer than a day. Though this longer-timescale variability is a key cost driver at high penetrations on the grid, it can be attenuated by blending the two resources owing to their strong seasonal anticorrelation.

Key-words: solar resource, wind resource, irradiance, high-penetration, storage, variability, firm power generation

1. Introduction

Both wind and solar PV resources are intermittent, driven by weather and seasons. Their high penetration in the generation mix implies mitigating intermittency and/or its impacts. The cost of the strategies and technologies to firm up these intermittent resources -- storage, geographic dispersion, overbuilding, and load flexibility – depends on their inherent variability (Perez et al., 2018).

The variability of solar and wind resources has been and continues to be a frequent topic in the literature. Many contributions have analyzed and documented the synergy between the two renewable resources on multiple temporal and geographical scales -- e.g., Prasad et al., 2017. Several publications, including by the authors (Perez et al., 2016) have documented the spatial smoothing effect in relation to time scale, and the possibilities of optimizing geographic dispersion to minimize variability -- e.g., Xuemei et al., (2018). The subject of long-term (inter-annual) variability and future resource evolution is also a well covered topic -- Gueymard & Wilcox, (2011), Krakauer & Cohan, (2018). The issue of resource integration and variability mitigation at multiple time scales, either on the demand or the user-side, is a fast growing field of investigations including by the authors (Perez et al., 2013). These contributions tend to center on strategies to economically maximize renewables integration with e.g., storage and/or demand side management that can be informed by short term ramp/fluctuations forecasts -- e.g., Shahriari & Blumsack, (2018).

Comparatively fewer studies have focused on the variability metric itself and on its underlying temporal and spatial fundamentals. The studies of Graabak & Korpas, (2016) on short-term variability characterization, Roy et al., (2018) on longer-term variability impact on islanded grids are two recent examples in this direction. On the solar front, the authors have contributed extensively to this subject by proposing variability metrics (Hoff & Perez, 2010) and quantifying the influences of temporal and spatial scales from minutes to years and from single locations to continents (Perez, 2018).

In this paper, we take advantage of experimental data developed for a grid integration study in the State of Minnesota (MDC, 2019) to examine and contrast wind and solar resource variability on multiple time scales ranging from one hour to several months.

2. Methods & Data

<u>Quantifying variability:</u> Equation (1) states a widely used and accepted metric to quantify an intermittent resource's power output variability for a given time scale Δt – see, e.g., Hoff & Perez, 2010.

$$\text{Power Variability} = \sigma(\Delta\rho\Delta t) = \sqrt{(\mathrm{Var}[\Delta\rho\Delta t])} \qquad (1)$$

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Where $\Delta\rho_{\Delta t}$ is the difference in nominal power generation [the ramp] between two consecutive time intervals.

Other indirect gauges of intermittency/variability often used by the utility industry include the resource's capacity factor. The capacity factor of a power plant or a fleet of power plants is the ratio between the mean power output and the rated (peak) power output of that plant or fleet. A high capacity factor is generally associated with low variability – e.g., a capacity factor of 100% implies an "always-on" resource, i.e., without variability.

Quantifying correlation: Equation (2) states a widely used and accepted metric to quantify the correlation between to variable timeseries at a time-averaging interval Δt – see, e.g., Hoff & Perez, 2010.

$$\text{Power Correlation} = \mathrm{cor}(\Delta\rho solar|\Delta t, \Delta\rho wind|\Delta t\ )$$

$$= \mathrm{cov}(\Delta\rho solar|\Delta t\ , \Delta\rho wind|\Delta t) \div [\sigma(\Delta\rho solar|\Delta t,), \sigma(\Delta\rho wind|\Delta t)] \qquad (2)$$

Where $\Delta\rho_{solar|\Delta t}$ and $\Delta\rho_{wind|\Delta t}$ respectively reflect the differences in nominal solar and wind power generation [the ramp] between two consecutive time intervals.

This power correlation allows us to see at which timescales the fluctuations in wind and PV output are likely to constructively or destructively interfere with each-other. For instance, it is often said that the wind blows more strongly in the winter than in the summer and more strongly at night than during the day. The sign of the correlation (negative or positive) at these different timescales will allow us to see whether or not this is the case in the area of study.

Experimental data: We use three years' worth of hourly statewide electricity production for both wind and solar (2014-2016). For wind, these experimental data consist of the actual metered production of the largest wind farms connected to the State's power grid. The total installed capacity of these wind farms amounted to roughly 4.5 GW in 2016. Time/site-specific solar resource data are derived from satellite remote sensing via SolarAnywhere (2019) and integrated over the State to match the wind geographic distribution. The data reflecting both PV and wind production are normalized to reflect the output in watts of one kilowatt of each resource.

3. Results

Capacity factors: The annual capacity factor extracted from the state's wind farms is nearly 37%. The simulated PV production amounted to 1,640 kWh per kW, i.e., a capacity factor of ~19%. Thus, using the capacity factor as measure of intermittency, wind is considerably less variable than solar in this considered Great Plains region, a region that has sometimes been called "the Saudi Arabia of Wind Power".

The seasonal capacity factor profiles are shown in Figure 1. Each point represents a 30-day moving average for the considered resource. Both wind and PV exhibit a nearly 1 to 3 excursion between minimum and maximum production periods. Interestingly, these seasonal production profiles are almost in opposition of phase, qualitatively suggesting that a combination of both technologies would be more stable on a yearly basis than either one, confirming many observations on this subject.

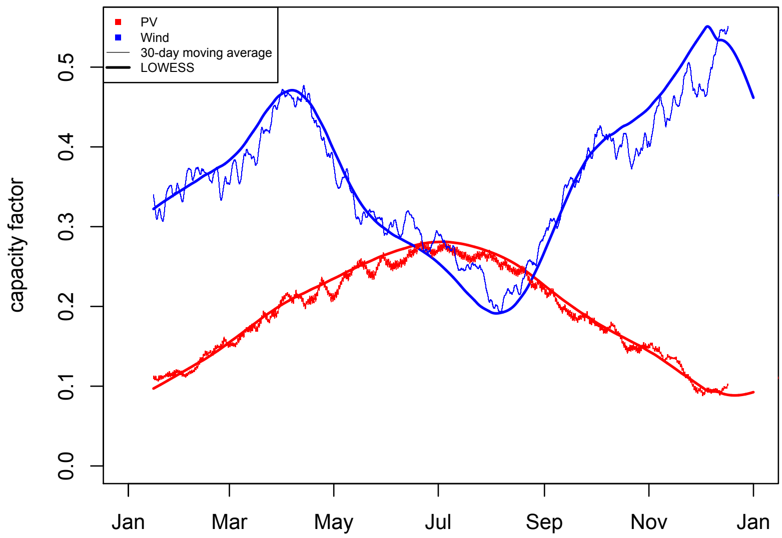

Fig. 1: Mean capacity factors for PV and wind using a 30-day moving average and a LOWESS smoother to highlight the trend

__Variability Metric__: In Figure 2, we report the variability of statewide-distributed wind and solar resources derived from equation 1. We considered time scales Δt ranging from one hour to one year, including all possible Δt groupings over the considered three-year period.

Results show that for short time scales, below ~ 12 hours, the variability of PV is much higher than the variability of wind – a result of solar geometry-induced steep morning and afternoon ramps for PV. However, for longer intervals, the variability of PV is consistently lower than wind's. Very long-term variability (Δt> several months) is comparable for both resources – this was qualitatively evident in Figure 1 where both resources showed comparable yearly min/max ratios.

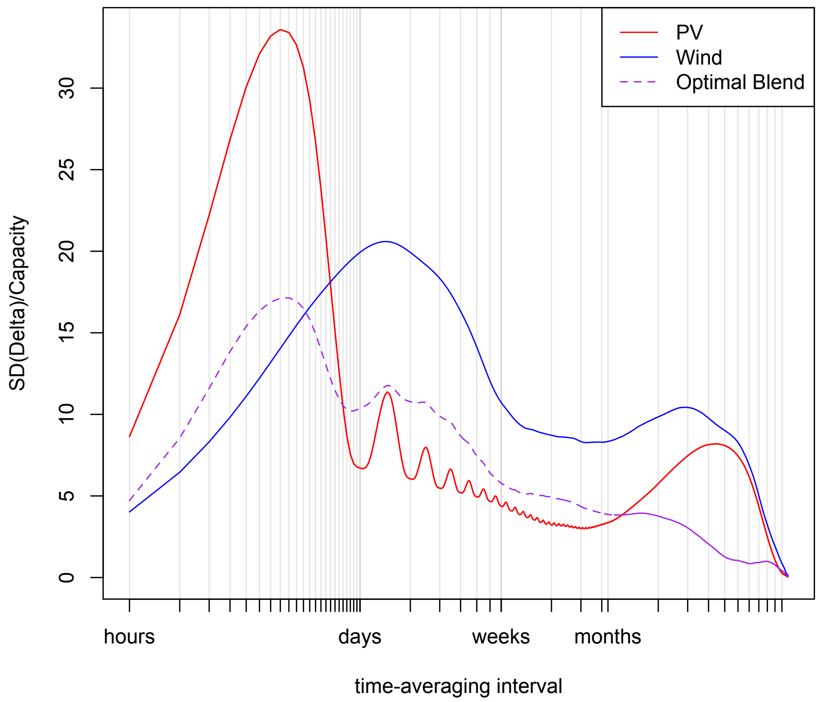

Fig. 2: σ(ρ) as a function of Δt for wind, PV and a 50/50 blend of the two.

Correlation Metric: In Figure 3, we report correlation in change characteristics between the solar and wind resources at different timescales with timescales at which wind and solar are positively correlated highlighted in blue and where they are negatively correlated highlighted in red. As with the variability characteristics, we considered time scales Δt ranging from one hour to one year, including all possible Δt groupings over the considered three-year period.

Results show that as expected, wind and solar are negatively correlated at the sub-diurnal level, indicating the wind does blow when the sun does not shine at these timescales. Of greater interest is near-perfect (-100%) seasonal anti-correlation seen peaking at roughly the half-year (6-month) mark. As storage costs and or capacity oversizing costs needed to bridge this seasonal gap are expensive, blending these two resources in roughly even proportions will leverage this anti-correlation and therefore yield a significantly lower cost as a result.

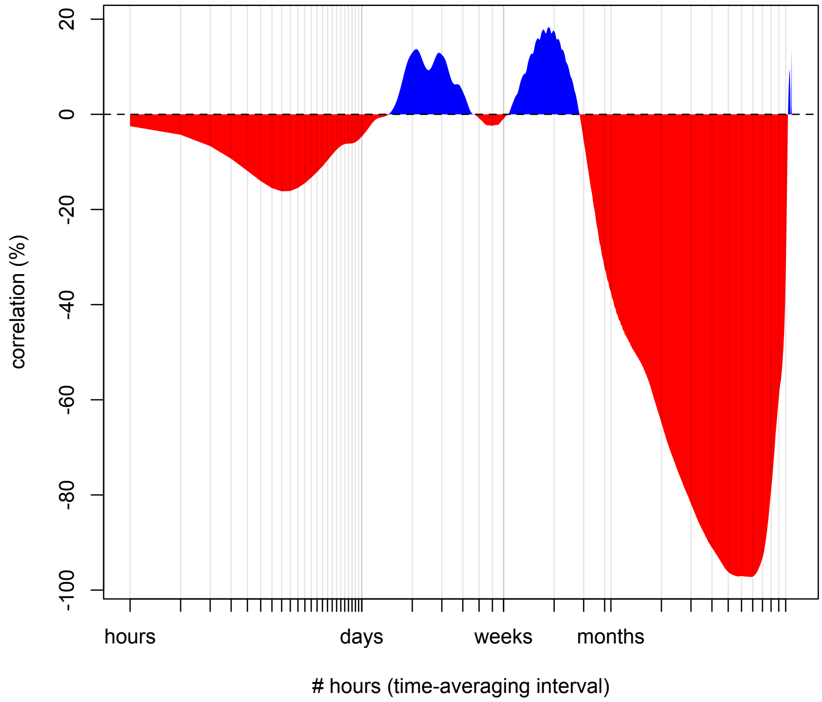

Fig. 3: Correlation between the changes in wind and solar resource at different time-averaging intervals. Red indicates negative correlation between wind and PV and blue indicates positive correlation.

4. Conclusions

From a cost perspective, high penetration renewables are driven by longer periods of imbalance. Although the variability of PV is very high for sub-diurnal timescales (owing largely to the rising and setting of the sun), the variability of wind is higher at nearly every other timescale. The more these longer-timeframe variabilities can be mitigated, the cheaper the cost of serving load. Wind and solar are strongly anti-correlated at the seasonal level in the state of MN, meaning that the imbalances that the grid has to deal with at higher penetrations of these two resources are significantly attenuated the more their relative capacity outlays are balanced. As the seasonal imbalances are reduced, the amount of storage capacity required to ride over this variability is equally reduced, therefore greatly reducing the cost profile of achieving high renewable penetration in the state.

5. References

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