On the Complementary Variability of the Solar and Wind Resources

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***Abstract*— The variability of large-scale, distributed wind and PV generation across the continental US is evaluated and contrasted. We analyze single year of hourly-interval, time-synchronous wind power production simulated from ERA-5 and PV production simulated with SolarAnywhere™. We examine the way in which the variability (as identified with a COV) of each resource changes with both temporal scale (time-averaging intervals from 1-8760 hours), spatial scale (spatial-averaging from 1 to 8e6 km^2) and location (across the CONUS). We empirically show that though the variability of solar power is much more significant than that of wind at sub 24-h timescale, wind exhibits significantly more variability than solar at all timescales longer than a day. We show that spatial averaging significantly reduces the variability of the aggregate wind resource, much more so than for solar. The implications with respect to the energy transition are discussed.**

Keywords*— *firm power, PV, wind, grid integration, storage, implicit storage, variability.

I. Introduction

Both the wind and solar resources are intermittent, driven by weather and seasons. Their integration in the generation mix implies mitigating intermittency and/or its impacts. The cost of the strategies and technologies used to firm up these intermittent resources -- storage, geographic dispersion, overbuilding, dispatchable backup (e.g. efuels) and demand flexibility – depends on their inherent variability [1].

The variability of solar and wind resources has been and continues to be a frequent topic in the literature. [2-4,7] Many contributions have analyzed and documented the synergy between the two renewable resources on multiple temporal and geographical scales. Several publications, including by the authors [5] have documented the spatial smoothing of variable renewable resources in relation to time-scale, and the possibilities of optimizing geographic dispersion to minimize variability [6]. The subject of long-term (inter-annual) variability and future resource evolution is also a well-covered topic – [7,8]. 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 [1]. 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 [10].

Comparatively fewer studies have focused on the variability metric itself and on its underlying temporal and spatial fundamentals. Several studies on short-term variability characterization [11], on longer-term variability impact on islanded grids [13] are two such examples in this direction. On the solar front, the authors have contributed extensively to this subject by proposing variability metrics [12] and quantifying the influences of temporal and spatial scales from minutes to years and from single locations to continents [4].

II. Methods

Data: In this paper, we pull wind resource data for 2023 at the ~25km, hourly resolution from ERA5 and simulate wind power production using conventional wind power curves at 100m hub height (Fig. 2). We pull solar resource data at ~10km, hourly resolution from SolarAnywhere and simulate PV power production reflecting fixed, equatorial-facing latitude tilt systems with no inverter clipping (Fig. 1). We have a list of centroids across the US, displayed by the yellow crosses on Figs. 1 around which, we calculate hourly-interval averages corresponding to window sizes (in km) 1x1, 3x3, 10x10, 23x23, 43x43, 77x77, 137x137, 276x276.

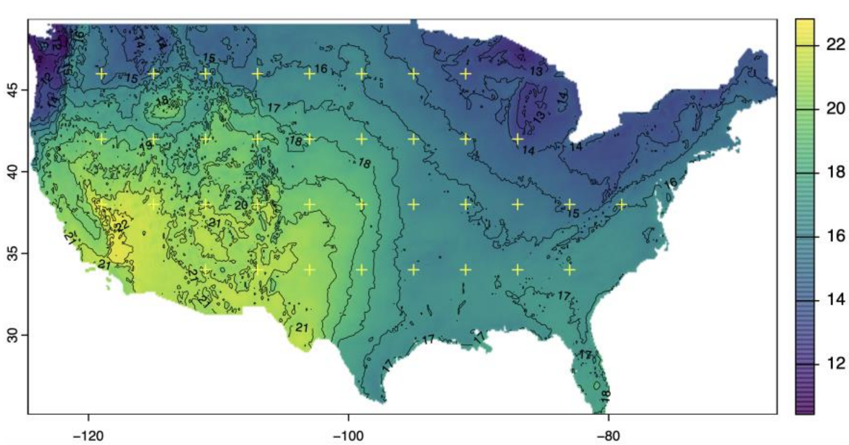

Figure 1: 2023 PV capacity factor at interpolated from simulated 10km SolarAnywhere data with centroids under investigation as yellow crosses.

Calculating Variability: Equation (1) states a widely used and accepted metric to quantify an intermittent resource's (R) power output variability for a given time scale Δt. [2-11]

$$\text{Power Variability} = \sigma(\Delta R_{\Delta t}) = \sqrt{Var[\Delta R_{\Delta t}]} \quad (1)$$

Where $\Delta R_{\Delta t}$ is the difference in nominal power generation [the ramp] between two consecutive time intervals at the timescale indicated by Δt.

A resource's capacity factor is also commonly used to assess variability. 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. However, this doesn't paint the entire picture as one can achieve the same capacity factor with very different characteristics of this variability; e.g. 50% capacity factor could reflect a plant operating at max output solely during 6 months of the year *or* at across 12 hours each day; reflecting very different load-serving capabilities.

In this paper, we calculate this statistic for Δt's stretching from 1h to 1d to 1w to 1m to 1y for both wind and solar power and both for Wind and PV.

Additional Analysis: Given the spatial scope of this paper across the continent, we also investigate the influence of spatial scale on the variability signature; calculating statistics for wind and solar across the aforementioned window sizes surrounding the centroids pictured in Figs. 1 & 2.

III. Results

In this abstract we present a selection of key results for the variability signatures we have calculated. In Fig. 3 is shown the 30-day moving average of solar and wind power production at a single site closest among the studied centroids to the center of the continental US. Notably, the wind capacity factor is over double the solar production save a one-month period in late august. There is also a much more significant seasonal variability apparent in the wind production than the solar production. The subplot at the right of Fig. 3 shows density plots of the monthly variability for each resource at this monthly timescale with power variability indicated by the dotted horizontal lines. Month-month variability for wind power production (8.9%) is over 4x the month-month variability for solar power production (2.1%) at this location.

How does variability of solar and wind power production at this location change as a function of timescale? Figure 4 introduces variability characteristic curves for solar and wind at this location. The y-axis indicates the power variability, and the x-axis indicates the time-averaging interval for which the corresponding variability is calculated on a log scale. The respective variabilities at 1h, 1d, 1w and 1m are called out with solid dots while the maximum variabilities and the timescales at which they appear are called out with circles of the same color. Of note is that solar is significantly more variable than wind at the sub-daily timescale while wind is more variable than solar at timescales beyond 13h.

The solar resource is most variable at this location from one 8h period to the next; this peak is present thanks to the deterministic diurnal variability of the solar resource. The wind resource is most variable at the 32-hour time averaging interval; likely reflecting the temporal cadence of weather fronts passing through the region.

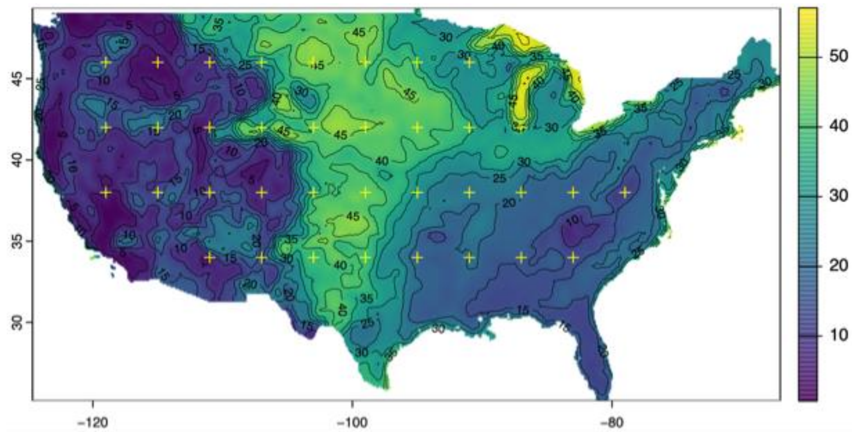

Figure 2: 2023 Wind capacity factor at interpolated from simulated 25km ERA-5 data with centroids under investigation as yellow crosses.

One also sees a smaller peak in variability signature at the 4–5-month interval owing to the seasonality of the wind and solar power outputs. Note that the red curve indicating the solar variability signature does not have nearly as pronounced a seasonal signature as wind variability. This is because we are simulating a fixed latitude-tilt system which increases winter production thanks to the tilt and thereby reduces seasonal variability at this timescale.

Table 1 indicates the way in which variability of solar and wind power changes as a function of both spatial scale

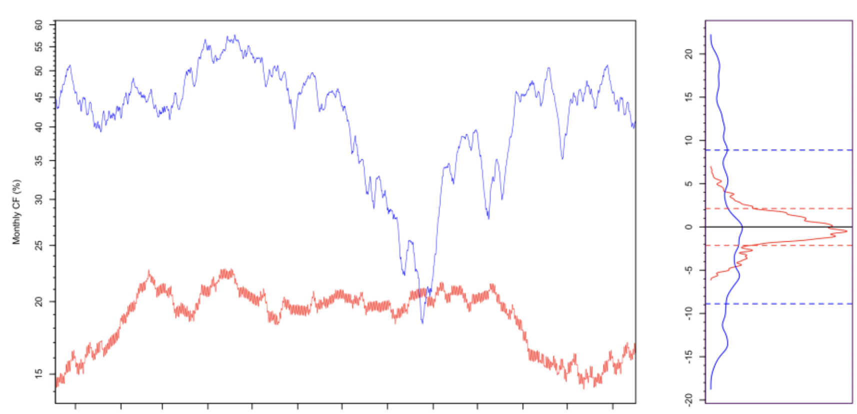

Figure 3: 2023 solar (red) and wind (blue) 30-day MA capacity factors across 2023 at 38°N, 99°W. Subplot at right shows corresponding probability distribution plots of the monthly variability for each resource (ΔR_{30d}). Dotted lines indicate mean +/- 1σ.

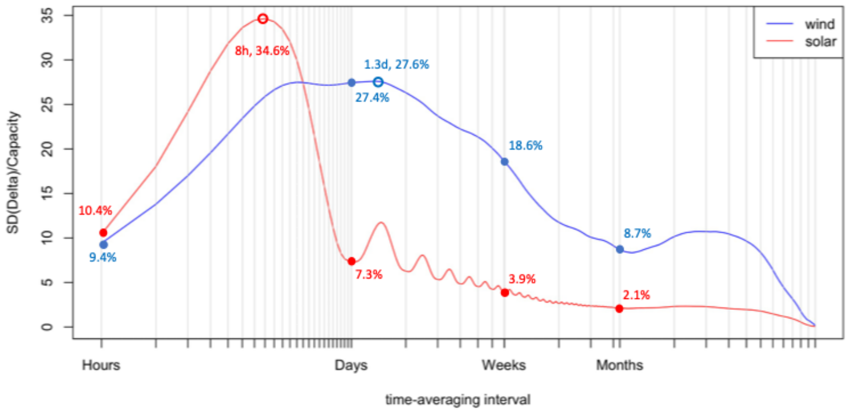

Figure 4: 2023 solar (red) and wind (blue) variability signatures as a fn. of timescale with variability at key time-averaging intervals called out.

TABLE 1

INFLUENCE OF SPATIAL SCALE ON VARIABILITY OF THE WIND AND SOLAR POWER PRODUCTION.

Δt	Window size	1x1	3x3	9x9	21x21	39x39	69x69	123x123	249x249
	Area (km^2)	1	9	81	441	1,521	4,761	15,129	62,001
Hourly	Wind	9.40%	9.40%	8.24%	6.06%	4.98%	3.94%	2.81%	1.74%
	PV	10.43%	10.12%	9.81%	9.55%	9.28%	8.96%	8.53%	7.88%
Daily	Wind	27.43%	27.43%	27.47%	25.89%	23.91%	20.25%	15.10%	9.73%
	PV	7.36%	7.34%	7.15%	6.64%	5.95%	4.90%	3.62%	2.20%
Weekly	Wind	18.61%	18.61%	18.71%	17.76%	16.77%	14.54%	11.31%	8.53%
	PV	3.93%	3.90%	3.86%	3.67%	3.40%	3.02%	2.39%	1.73%
Monthly	Wind	8.69%	8.69%	8.78%	8.50%	8.35%	7.95%	7.30%	6.18%
	PV	2.15%	2.17%	2.16%	2.10%	2.06%	2.02%	1.92%	1.88%

(columns) and selected temporal scales (rows) centered at 38°N, 99°W. The larger the spatial extent across which wind and solar power are spread, the lower the aggregate variability. Wind sees a larger reduction in variability than solar at all time-averaging intervals when moving from the smallest to the largest area studied save weekly where they experience roughly the same reduction

IV. DISCUSSION

This study evaluates the variability of wind and solar power across temporal and spatial scales in the continental U.S., providing insights into their integration into a renewable grid. Our results show distinct variability patterns, key for grid stability and energy strategy.

Solar power is more variable at sub-daily timescales due to the predictable diurnal sunlight cycle, with sharp fluctuations during the day and low output at night. Wind variability is more prominent at timescales beyond 24 hours, driven by large-scale weather systems. Wind peaks at the 32-hour timescale, while solar peaks at 8 hours. These complementary patterns suggest that combining wind and solar can balance their fluctuations, enhancing grid stability and reducing the need for balancing strategies.

Spatial averaging reduces wind variability significantly, as it smooths fluctuations from large-scale weather systems. For solar, spatial averaging has less impact since solar variability is more localized. This indicates that solar intermittency may require additional strategies to absolve, particularly at the diurnal scale. Certainly, energy storage is critical to ride through the night.

Combining wind and solar reduces overall variability, stabilizing grid operations. Wind can fill gaps when solar drops, and solar can do the same for wind. However, while spatial averaging reduces wind variability, solar variability requires strategies like energy storage, overbuilding, or hybrid systems. Long-duration balancing strategies like implicit storage is essential for bridging gaps during low-output periods, particularly in winter.

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