Emerging Opportunities in Low-Frequency Variability of Renewable Resources: A 7-Year Update

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Abstract. Some recent developments in quantifying, applying, and forecasting variability in renewable resources (especially solar and wind) at timescales of months to years are reviewed. These include detailed studies of national-level resource variability, methodological work on quantifying variability and applying risk assessment to optimize and manage power grids, and work on the potential and benefits of long-range forecasting. Likely directions for future progress include data fusion, nonparametric statistics, machine learning, and joint consideration of multiple supply, demand, and storage modalities.

Keywords: resource assessment · solar energy · wind energy · value at risk · seasonal forecasting · machine learning

1 Introduction

Published in summer 2017 and based on work presented at the 2016 ASES conference, the paper "Interannual variability and seasonal predictability of wind and solar resources" [1] systematically examined interannual variability in a global reanalysis (MERRA-2) of grid-scale monthly-mean solar and wind resource (operationalized as surface incident shortwave flux and wind speed at 50-m height, respectively). Its goals were to quantify this meteorological interannual variability in renewable solar and wind resources, considering also whether anomalies in wind and solar show positive or negative correlations, and to correlate this variability with major global climate modes that might offer an avenue to forecasting it.

This research extended a previously published case study of a multi-month period of low windspeed which affected power generation over the western and southern United States in the first half of 2015, and which was associated with a Northern Pacific Mode of warming in the offshore Pacific Ocean (but not clearly

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related to El Niño, which shows little correlation with windspeeds in the affected area) [2]. This event featured wind speeds regionally up to 20% below average over a multi-month period, motivating a proposed research agenda of verifying the patterns seen in this global data locally under particular site configurations and networks and developing and quantifying the value of options for acting on seasonal energy forecasts that could provide early warnings of such marked departures from the climatological renewable energy resource.

Seven years after the initial ASES presentation, the opportunity is taken here to review some of the applications and extensions of this work in the years that followed, as reflected in peer-reviewed journals, conference proceedings, and published theses. Finding recent research that has taken this direction began with the works citing [1] according to Google Scholar, augmenting these in turn with the most relevant materials cited by or citing them. While this will not cover all advances in the field, the sampling is meant to provide a sense of the main directions and extents of progress in recent years and provide the basis to identify gaps and promising directions for more detailed investigation.

2 Review of Selected Work

2.1 Quantification of Variability

One area of progress in recent years has been in detailed national-level studies of solar or wind variability. For example, [3] consider the interannual coefficient of variation of both global horizontal irradiance and direct normal irradiance across North and Central America using the National Renewable Energy Laboratory (NREL) satellite-derived National Solar Radiation Database (NSRDB). Interannual variability is relatively larger for normal as compared to global irradiance, and, similar to [1], the Midwest and Northwest regions of the United States had particularly high interannual variability in solar radiation in the winter months. [4] map the coefficient of variation of mean annual windspeed over India using the new reanalysis ERA5 [5]. [6] studies interannual variability in annual mean windspeed data collected for roughly one decade at different heights from weather stations spread across South Africa as part of the Wind Atlas for South Africa project. The author found significant increasing windspeed trends at two of the stations. [7] studies interannual variability in monthly power production of wind farms across the United States.

2.2 Methodological Advances

Methodological work on how to best quantify interannual variability remains important, and a number of noteworthy contributions can be highlighted. As part of the first author's doctoral work at the University of Colorado, [8] compare measures of interannual variability in MERRA-2 windspeed to examine which is the best predictor of variations in actual monthly power generation at wind farms across the United States, recommending the use of a robust coefficient of variation that uses the mean absolute deviation and the median instead of the standard deviation and mean. They find that this measure requires around 10 years of windspeed data to be estimated with 90% confidence to within 10%. Similarly, [9] study wind data at 2 sites in Brazil to estimate the effect of longer monitoring period in decreasing uncertainty related to power generation at a given site.

One area of methodological development has been in assessing the complementarity of multiple renewable energy resources, particularly wind and solar, from the standpoint of the coherence of their low-frequency variability. In an ISES Solar World Congress 2019 paper, [11] analyze the variance spectrum across timescales from hours to years of wind power data alongside simulated solar generation in Minnesota state, finding that the combination of wind and solar has lower variance at daily and yearly scales due to stronger wind at night and winter when solar is unavailable. A study for Texas state [12] also finds complementarity between wind and solar generation, along with favorable effects of geographic dispersion of the generating facilities. In Germany, on the other hand, complementarity between wind and solar resource, as assessed by fitting a bivariate copula, cannot overcome the large interannual variability seen for wind, and within-country geographic diversification doesn't help much [13].

2.3 Energy System Analyses

Another category of studies considers variability in solar and wind resources as part of an analysis of particular power grids, including their effect on the sizing and management of storage and fuel backups. In an IEEE Power & Energy Society conference paper, [14] present a discrete convolution approach that uses empirical linear quantile models to relate wind, sun, and energy demand in an isolated Australian minigrid to quantify the probabilities of system failure, concluding that the share of renewables could be increased while reducing dependence on fossil fuel backup for greatly reduced cost. Also as part of the same first author's Stanford doctoral dissertation, [15] consider optimal combinations of energy generation and storage for maintaining specified reliability levels in the New England power grid, again using historical data to estimate models for correlations between, for example, wind and solar generation. [16] simulate 1000 years of California electricity supply and wholesale price using stochastic weather inputs in the California and West Coast Power System (CAPOW) computer model. In their simulations, highest prices were associated with hot and dry years that have high energy demand and low hydroelectricity generation, though this could presumably be overcome by additional large solar deployments and diurnal storage that would supply ample energy under sunny summer conditions. In a master's thesis, [17] considers sub-hourly wind and solar data from generation facilities in Nova Scotia province, for which both wind and solar generation showed lower capacity factors during the winter peak demand period, finding that wind generation plus battery storage seemed more economical for reducing fossil fuel backup generation than solar generation, but highlighting the need for additional years of data to better understand meteorological variability.

Moreover, an International Conference on Machine Learning paper [18] discusses the development of a long short-term memory neural network regression model for estimating United States regional electricity demand as a function of temperature to facilitate studying meteorological factors affecting energy demand alongside supply, finding that the relationship between electricity demand and temperature is stronger in summer than in winter.

2.4 Long-Range Forecasting

Particularly intriguing is emerging work on the extent to which seasonal forecasting [19,20] could aid in managing renewable-based power systems. [21] show a geographically complex relationship between climate modes of variability, particularly the North Atlantic Oscillation (NAO), and winter sunshine over the British Isles, with positive NAO being associated with more cloud on the western side of both Britain and Ireland but less cloud in their eastern sides. [22], part of the first author's doctoral thesis, considered risk of winter wind generation shortfall during the daily evening consumption peak in France, finding that this risk is correlated with large-scale atmospheric circulation patterns and that it can be quantified with some skill at least one month ahead based on weather models. More comprehensive work on the benefits of forecasting to energy networks should include multiple renewable generation modes (wind, solar, hydroelectric, etc.) as well as demand (including its dynamic management at timescales of minutes to months) and various forms of storage.

3 Future Prospects

This unsystematic overview serves to illustrate the continuing interest in understanding low-frequency variability in solar and wind resource and its predictability. While the research summarized here has helped quantify the magnitude of interannual variablity and provided indications that it can be forecast at least a few weeks ahead, there is still a long way to go in quantifying the risks of large difference from normal in wind or solar over a given season and in providing early warning of such an event to minimize its impact on system reliability and cost. Progress in the coming years will include comparing and improving data on renewable resources (combining stations, satellites, and reanalyses); advances in statistical and machine learning methods of quantifying variability and correlation; predictability improvements from both dynamic and statistical seasonal forecast systems; and more sophisticated risk assessment amid a broader range of options and management strategies, which will also help better quantify the benefits of this research direction to different communities.

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