Solar Forecasting: Maximizing its value for grid integration

Introduction

The forecasting of power generated by variable energy resources such as wind and solar has been the focus of academic and industrial research and development for as long as significant amounts of these renewable energy resources have been connected to the electric grid. The progress of forecasting capabilities has largely followed the penetration of the respective resources, with wind forecasting having achieved a more mature state-of-the-art compared to its solar equivalent [Lew 2010].

Still in the last 5 years, there has been substantial and material progress in the state-of-the-art of solar forecasting [Kleissl 2016]. Numerical Weather Prediction (NWP) models became more sophisticated in assessing cloud interactions with aerosols; infrared satellite imagery allowed discovery of pre-sunrise cloud formations; advanced data processing methods such as deep machine learning became increasingly accessible; probabilistic forecasts began replacing deterministic ones; and, in balancing areas with high PV penetration, solar forecasts are now used operationally.

Bulk grid integration

As solar electricity penetration in the distribution grid is increasing, the power generated by those Distributed Energy Resources (DERs) needs to be taken into account in the operations and planning of IPPs, ISOs, and Balancing Authorities [Mills 2013]. Since the reliable performance of the bulk grid depends on the balancing of a continuously varying load with equal amounts of generation, knowledge of the load ahead of time (forecasting) is necessary for the economically optimal – and technically feasible – dispatch of generation sources.

Solar electricity generation presents two challenges to the process above. First, a very large fraction of it comes from distributed PV systems (DPV) that are connected behind-the-meter (BTM) and are thus only visible to the system operator as load. This gives rise to the "net load" curve which represents passive load net of (i.e. "masked" by) solar PV electricity generation. Second, PV plants, even utility-scale that are connected directly to the distribution or transmission systems as generation assets, are not normally dispatchable due to the intermittency of their fuel (solar resource).

The first challenge manifests as load variability that cannot be adequately described by the traditional load forecasting techniques, mainly because of the uncertainty associated with forecasting solar irradiance. The second one requires that any imbalances due to over/under-generation by PV plants have to be compensated by ramping other dispatchable resources (reserves) and/or by curtailing solar generation where possible, resulting in increased operational costs. Those costs comprise fuel costs from expensive generators and start & shutdown costs for fast-responding generators and they scale with increased solar penetration [Brancucci Martinez-Anido 2016]. Both challenges can be mitigated by an improved-accuracy forecast of the solar power generation.

Because solar power generation depends mostly on incident irradiance, the cost-efficient integration of significant amounts of solar electricity in the grid ultimately depends on the ability to forecast accurately solar irradiance in the plane of the array (also known as GTI: Global Tilted Irradiance) for flat plate non-concentrating collectors or the Direct Normal Irradiance (DNI) for concentrating collectors – at various time horizons.

However, knowledge of the future level of irradiance is not by itself adequate for the calculation of solar power output. Knowledge of the attributes of the interconnected systems (such as DC and AC nameplate capacities, orientation, PV module and inverter properties, etc.) is also necessary, and that information can be largely elusive, inaccurate, or outdated for BTM systems. Therefore, an advanced capability of modeling the output from large numbers of PV plants is also essential for the network operator [Kankiewicz 2015].

At the same time, efficient operation of the grid requires the accurately projected contribution of solar generation to be presented in a manner that allows error-free, optimally-timed decision making by the operators and/or the automated systems they use during Unit Commitment and Economic Dispatch operations.

In summary, from a load balancing perspective, the reliable and economically optimal operation of an electric grid with high penetration of solar (especially distributed solar) generation depends on:

1. Accurate forecasting of the solar irradiance and its evolution in time over the area of interest, with 1-km spatial resolution and temporal resolutions that range from 5 minutes to hourly for time horizons between 0 and 72 hours , with 1-6 hour and day-ahead horizons being of particular importance;
2. Accurate forecasting of solar power output (and its evolution in time, including variability) over the area of interest, including an estimate of the forecast's uncertainty; and
3. Effective integration of the projected solar power output information with the systems used to manage and operate the network and other generation sources.

The accuracy of the irradiance forecast at a given location over any time horizon depends primarily on the accuracy of predicting the opacity of any clouds that might be present in the path between the solar disk and the solar array. Despite the considerable recent progress in solar forecasting with a variety of methodologies that are optimized for different forecast horizons (Figure 1) the forecast skill is affected by specific local conditions, such as the marine layer in the coastal region of California [Mathiesen 2013]. As for particular cloud types and sizes, even if they are detected it can be more challenging to predict their evolution. Additionally, the spatial resolution of these techniques may be limited by computational capacity.

Therefore, improvements in cloud detection, cloud creation and dissipation, and modeling of atmospheric physics are still active areas of research.

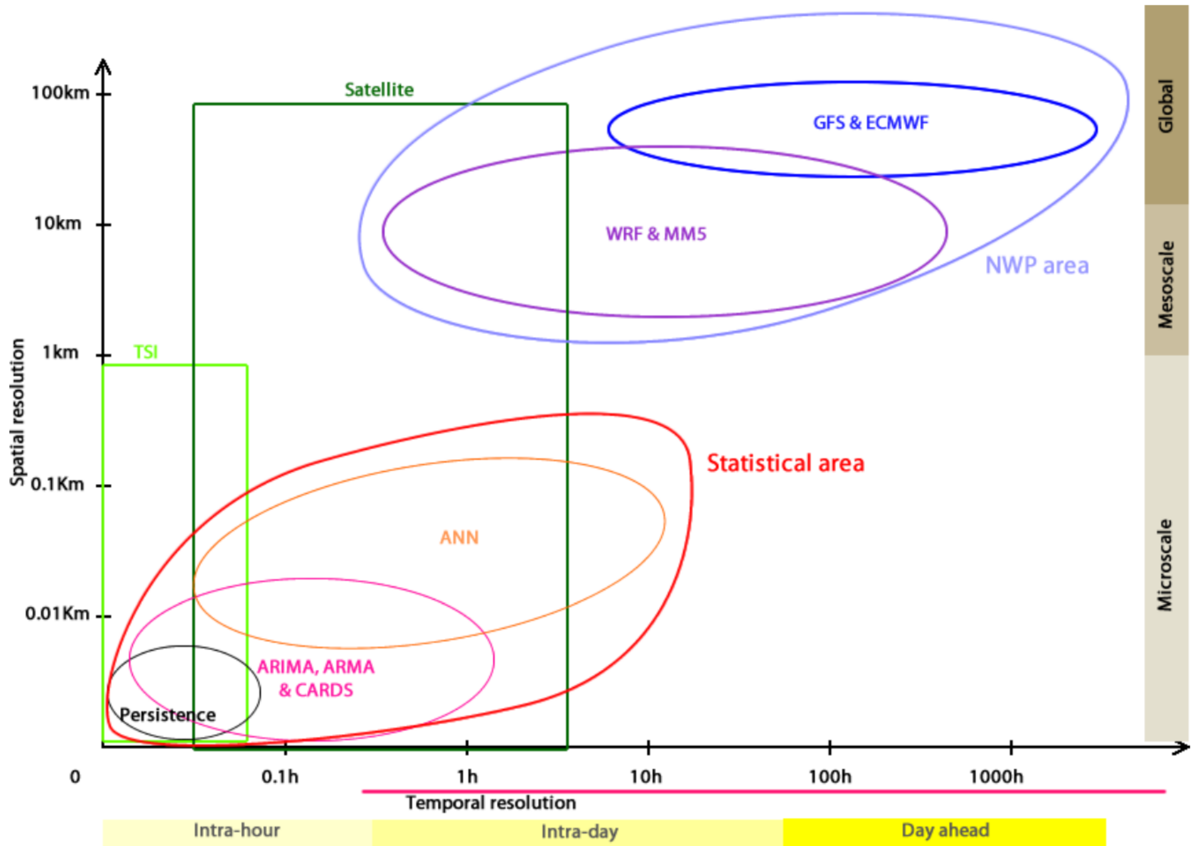

Figure 1: Forecast model classification based on temporal and spatial resolution [Diagne 2013]

Large-scale, high-cost events

Even though select ISOs, Balancing Authorities, and IPPs have begun using solar power forecasting products, their integration into the workflow, which encompasses unit commitment and economic dispatch, is not yet uniform. A probable cause for the slow integration is that the penetration of BTM solar is relatively low in most balancing areas (with the exception of Hawaii and California) and therefore the need for such a capability is not yet urgent. Another cause may be the lack of clarity regarding the economic value of solar power forecasting. Recent DOE-funded research has attempted to quantify the value of forecasting by estimating the savings afforded by increased accuracy, and therefore avoiding a conservative (and therefore unnecessarily costly) scheduling of reserves [Zhang 2015, Brancucci Martinez-Anido 2016].

A particular case where improvement of accuracy can result in significant savings corresponds to large-scale weather events that may dramatically reduce (or increase) the output from solar systems in very short time frames [Zhang 2015]. Such cases usually manifest during low gross load seasons with significant solar generation, e.g. spring time in moderate latitudes. This combination would make the net load curve attain the shape described as “duck curve” by CAISO[1] or “Nessie” by HECO[2]: a sharp increase in net load as the contribution from BTM generation drops precipitously in the late afternoon.

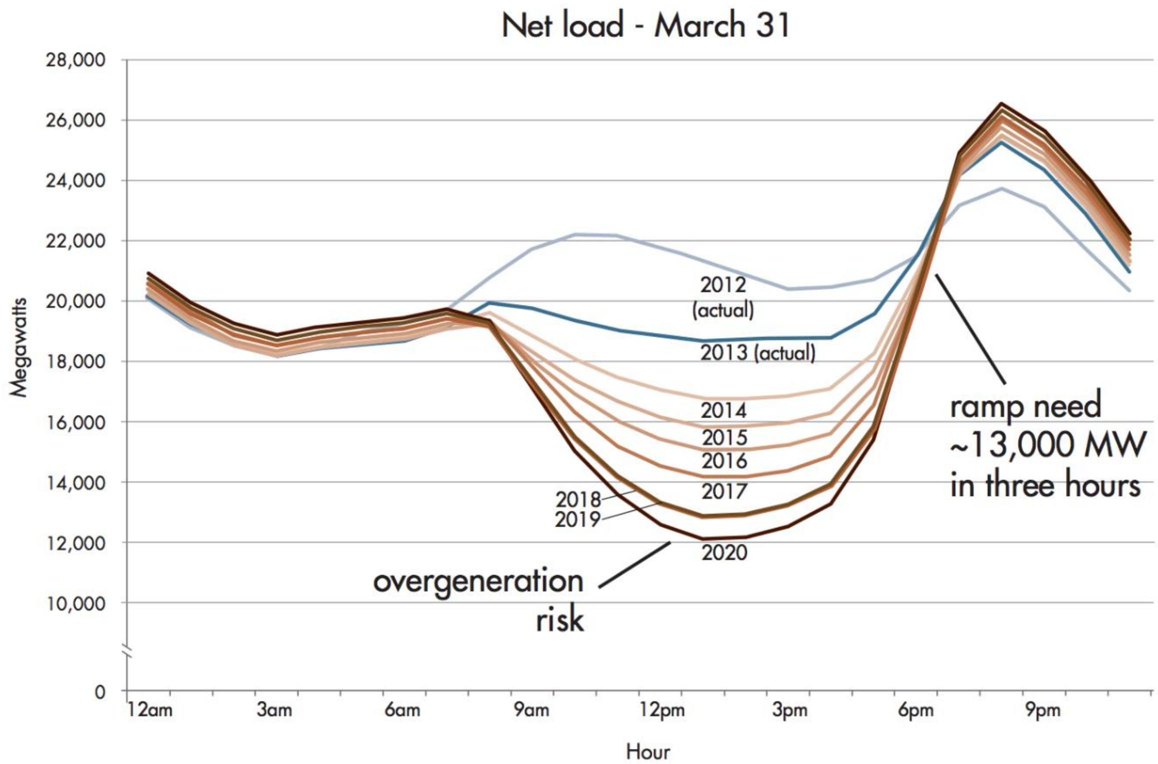

Figure 2: "Duck curve" from CAISO net load actual records and future projections

The balancing authority normally expects that behavior and has scheduled the appropriate conventional generation sources to manage the steep ramp in the net load. However, if a storm system moved across the territory during the hours of peak solar energy production (e.g. between 10am and 2pm Local Standard Time), then this steep ramp in net load would appear hours earlier than normally anticipated and it would be very expensive to compensate without an accurate forecast of its occurrence. An example case for CAISO investigated in [Zhang 2015] shows that a 35% improvement in ramp forecasting accuracy (when coupled with a 18% uniform accuracy improvement) can reduce the annual cost of spinning reserves by $5M (a 25% decrease) using an average hourly cost basis of $10.11 per MW of spinning reserves and assuming a solar nameplate capacity of 4.1 GW (9% of peak load).

Such large-scale events with stochastic character (as opposed to the deterministic character of the late afternoon ramp) will have an outsized impact with a high penetration of solar power (e.g. 20% or higher of daily peak load), so it is necessary to acquire the ability to accurately forecast the timing, location, and

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[1] https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

[2] http://www.greentechmedia.com/articles/read/hawaiis-solar-grid-landscape-and-the-nessie-curve

impact of their occurrence well in advance (12-24 hours) of the event in order to schedule contingency generation at an economical price.

Due to the type of variability exhibited by solar power – characterized by a probability density function with tails "fatter" than those of a normal distribution [Mills 2010, Golnas 2011] – as well as the cost associated with scheduling reserve capacity that may represent a significant fraction of the system's load, there is significant value in the early and accurate forecast of the tail events.

Therefore, a more targeted effort to accelerate the adoption of power forecasting products by the interested parties might center on the following:

A. Increased accuracy of forecasting large-scale events (corresponding to ramps that exceed the ramping capacity of thermal, non-peaker generators) at appropriate forecast horizons:
    - MAE<10% in 30-minute solar output for forecast horizons of 12-36 hours
    - MAE<5% in 10-minute solar output for forecast horizons of 1-6 hours

B. Improved integration in operational workflow through visualization of observed, historical, and forecasted output, including ramps, with probability bands with customizable confidence intervals

Distribution grid integration

The increasing amounts of solar generation connected to the distribution grid, whether residential, commercial and industrial, or utility scale, poses specific challenges to the distribution grid operators. These challenges are largely associated with the voltage at the point of interconnection (POI). For example, excessive solar power injected into the distribution grid during times of low demand can push the voltage at the POI high enough so that it causes reverse flow of power on a line or a feeder, thereby potentially interfering with the installed safety equipment which operates under the assumption that the power flow is unidirectional, extending radially from the substation to the consumer loads. In addition, the existence of uncontrolled generation downstream of the substation poses safety challenges during maintenance operations that require the de-energizing of feeders or lines. Finally, the fluctuation of solar power caused by rapid variability in the irradiance due to traveling, broken and opaque clouds (i.e. cumulus clouds), can cause voltage regulation devices, such as On-Load Tap Changers (OLTCs) to operate much more frequently than designed (in circuits with high PV penetration) and therefore reach prematurely the end of their useful life.

Variability forecasting

All these challenges can be mitigated by various combinations of inverter-firmware enforced rules, advanced inverter capabilities, upgraded distribution grid management equipment, communications, and software. The one challenge which can potentially be mitigated by forecasting is the one associated with the excessive wear-and-tear of the On Load Tap Changers (OLTCs). Since the root cause of this problem is the occasional extreme variability of solar resource at very high spatial resolutions, the ability to forecast such a regime could be used to engage or optimize the parameters of appropriate measures, such as OLTC control algorithms [Disfani 2015], or Volt/Var response curves. In more advanced environments, forecasting of solar power variability could inform the pricing (and value) of ancillary services, including energy storage, in the distribution grid.

The ability to use effectively a variability forecast hinges on using a metric that conveys usable information about the type of variability that will be experienced at a location over a specified interval – for example, average, maximum and minimum power, ramp rates, number or frequency of ramps, etc. The applicable time horizons for optimizing control parameters for OLTCs and inverters are relatively short (<1 hour) so techniques such as total sky imaging or high temporal resolution satellite imagery could be used effectively. For longer time horizons that would be applicable to participating in a distribution-grid energy and services market, techniques combining analog ensembles [Alessandrini 2015] with NWP modeling could prove suitable solutions.

Conclusion

The purpose of this paper is to instigate and inform discussions among the stakeholders involved directly and indirectly in the operation of an electric grid that is being transformed by the rapid growth of solar generation. A targeted technical workshop that will take place in Washington, DC, on August 3, 2016, will provide additional opportunities for constructive interactions through invited presentations and discussion groups. To further assist those discussions, we are including at the end of this document a list of questions aimed at the two major stakeholder groups: the solar forecast users (mainly Balancing Authorities and Independent Power Producers) and the solar forecast generators (mainly research institutions and private forecast providers).

The end goal of this effort is to help the DOE and the SunShot Initiative assess the state-of-the-art in solar power forecasting and identify the gaps and needs for further research in order to achieve cost effective, reliable, and safe integration of hundreds of gigawatts of solar energy into the U.S. electric grid.

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