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The effect of PV siting on power system flexibility needs

Michaelangelo D. Tabone [a,*], Christoph Goebel [b], Duncan S. Callaway [a]

[a] Energy and Resources Group, University of California at Berkeley, Berkeley, CA, United States
[b] Technical University Munich, Munich, Germany

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ABSTRACT

Locations of photovoltaic (PV) systems affect the variability and uncertainty of their power generation, and as a result the amount of flexible resources needed to balance supply and demand. However, studies on the integration of renewable electricity into power systems focus on the total amount of renewable generation, and not their locations. This paper uses a hidden state, spatial-statistical model to simulate how locational arrangements and balancing policies affect the need for reserves—load following and regulation—in California's power system when including 12 GW of photovoltaic generators and 9.5 GW of wind.

Our results show that locations of utility-scale PV systems significantly affect on the amount of reserves needed for balancing their variability and uncertainty. When PV is geographically dispersed the additional load following and regulation reserve needs are small; on average <1.2% and <0.05% of installed PV capacity respectively. These rise to 5.6% and 0.2% in centralized scenarios. Most the benefits of this dispersion can be achieved with relatively few, 25, systems. These are sized at roughly 500 MW each, which is about the size of the largest systems in California today. Almost all of the load following reserve need is driven by errors in the hourly forecasts of solar generation. These can be mitigated either by better forecasts, or dispersing plants.

Siting policies for PV must weigh system flexibility against other locational concerns, such as the energy and capacity value of the solar resource in an area. We find a small trade off between energy and reserves; where dispersed systems require less reserves but also have lower capacity factors than more centralized systems. However, we find a much greater trade-off between energy and capacity value in California; where the regions that produce the most energy on average—in the Mojave desert—tend to be cloudy during current peak demand hours, which occur during Summer afternoons.

1. Introduction

Renewable generation poses a dual challenge to electricity system planners and operators. It adds variability and uncertainty in electricity supply, while decreasing the number of on-line controllable generators that can be used to balance supply and demand. For electric power systems to rely primarily on renewable generation, flexible resources will be needed. These resources could be generators, consumers, or storage systems that can reliably increase or decrease supply or demand to maintain balance.

A number of renewables integration studies (Wu et al., 2015; Hummon et al., 2013; Ela et al., 2013; Lew et al., 2013; Energy, 2010; Corbus et al., 2010; Bai et al., 2007) investigate how increasing the amount of wind and solar generation will impact power system operations. Among other things, these studies estimate the amount of flexible resources needed to be held in reserve to respond to fast or unexpected changes in supply or demand. Notably, Wu et al. find that including the PV capacity amounting to 20% of peak demand in the Arizona Public Service territory results in increases in reserve needs by 2–3% of installed PV capacity (Wu et al., 2015).

Locations of wind and solar generators affect the need for flexibility. Renewable resources exhibit different amounts of variability and uncertainty regionally, and often renewable resources are spatially correlated. Spatial correlation implies that renewable generators located closer together are more likely to experience simultaneous weather events than those far apart. Thus siting PV systems in close proximity to one another may exacerbate events that need to be managed by the system operator, and the opposite may be true for systems sited far apart from one another.

Renewables integration studies often account for spatial correlation of PV generation; however deciding where to site new PV or transmission is not their focus. For example, Phase one of the Western Wind and Solar Integration Study uses spatial scenarios

* Corresponding author.

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to vary how much PV is sited by state. But within each state, PV is always sited according to the same principles (Energy, 2010). States are large enough that moving systems from one to another does not greatly affect the correlation between systems, but the spacing of systems within states will affect this correlation.

In this study we seek to answer questions about how siting PV will affect reserve requirements. For example: What are the implications of siting large amounts of PV at the same substation, or in the same county? Can utility-scale systems achieve the same benefits of spatial diversity that rooftop systems do? Do regions with low variability and uncertainty overlap with regions with high capacity factor, or with high capacity value? To our knowledge these questions have not been directly and systematically addressed in the literature. The answers to these types of questions could be important for regional transmission planning processes, such as those in California (California Public Utilities Commission, 2016).

1.1. Statistics of solar variability and uncertainty

A large body of prior work focuses on the spatial correlation of variability from wind and solar generation. See Lave et al. (2013), Mills and Wiser (2010), Perez et al. (2011) and Murata et al. (2009) for examples regarding solar with complete literature reviews, and Hinkelman (2013) and St Martin et al. (2015) for examples regarding wind. Most of these studies use spatial correlation functions to predict the standard deviation of variability or uncertainty from theoretical arrangements of PV systems (Murata et al., 2009; Perez et al., 2012; Lave et al., 2011), and do so accurately.

Despite knowledge of the standard deviation, it remains difficult to predict variability or uncertainty from PV in a way that is useful for power system operations or planning. System operators are concerned with high impact, low probability events which are defined by distribution tails—for example, system operators may plan to balance supply and demand in >95% of times. Mean and standard deviation completely parameterize only a few distribution shapes, most notably the Gaussian distribution. Unfortunately, the distribution of variability from PV has been shown not to be Gaussian in many studies (Mills and Wiser, 2010; Murata et al., 2009; Tabone and Callaway, 2013; Lave and Kleissl, 2013).

Two studies condition variability on hidden Markov processes to predict non-Gaussian shapes (Hummon et al., 2013; Wegener et al., 2012). However these models predict variability and not uncertainty in PV generation, and do so only for individual systems, without modeling spatial correlation of neighboring systems. Another strategy accounts for spatial diversity by smoothing the generation from a small PV system–or a single irradiance point sensor–to mimic generation from a larger plant (Lave and Kleissl, 2013; Marcos et al., 2011; Marcos et al., 2012). Different smoothing filters are applied at different time-scales to represent increased spatial correlation at longer timescales and vice versa. While this method accounts for smoothing in one utility-scale PV system, it does not model spatial correlation between multiple utility-scale systems, which is precisely what we would like to study in this paper.

Finally, the literature tends to focus on predicting statistics, and not on predicting the resulting effect on power system operations and planning. Two notable exceptions investigate the costs of mitigating ramps in solar generation. Mills and Wiser investigate the costs of managing changes in solar generation ramps when dispersing PV systems from 1 to 25 locations (Mills and Wiser, 2010), though this study focuses only on variability and not uncertainty, and does not account for intra-plant smoothing. Perez et al. investigate the costs of using electricity storage to maintain ramps in PV generation below a specified threshold (Perez et al., 2014), but do not investigate the effect of these ramps on power system operations.

We advance this body of work by applying modeling techniques from our prior work (Tabone and Callaway, 2015), in which we developed a statistical model that addresses these issues by (a) accounting for spatial correlation, (b) predicting metrics of variability and uncertainty that are directly relevant to grid operation and planning, and (c) predicting boundaries on distribution tails that are consistent with observed data. This paper makes use of this model to estimate how the spatial arrangement of PV in California may affect the need for reserves.

1.2. Predicting reserve need in renewable integration studies

Renewable integration studies treat reserve procurement in differing ways—driven both by the procedures of system operators and by the assumptions made in each study. For example, many studies define the amount of generation held in reserve to be constant throughout the year, or to be a fixed percentage of total load, wind, and/or solar in the system (Rothleder, 2011; Energy, 2010). In contrast, more recent studies define the amount of reserves procured each hour to be dynamic, reflecting varying expectations of load and renewable generation in each specific hour (Hummon et al., 2013; Ela et al., 2013; Wu et al., 2015).

Methods to calculate the amount of reserves to be procured—dynamic or constant—also vary. Most early studies used the *n*-sigma method, which defines reserve need to be *n* standard deviations of expected variability and/or uncertainty. If distribution shape of variability or uncertainty is Gaussian, the n-sigma method defines a confidence interval for reserve needs. However the distribution shape has been shown not to be Gaussian. It has heavier tails, signifying that extreme events are more likely than a Gaussian would predict (Holttinen et al., 2013; Milligan et al., 2011). Integration studies will often use an arbitrarily large *n* as a conservative approximation for boundaries on these wide tails.

More recent studies overcome this limitation by using alternative heuristics. For example, the 2nd Phase of the Western Wind and Solar Integration Study define regulation reserve procurement by the square root of the sum of squares of the 95th percentile hourly forecast errors for wind and solar (Lew et al., 2013). Wu et al. actually simulate 200 possibilities for reserve need at each interval, and procure reserves that will cover 95% of simulated need (Wu et al., 2015).

1.3. Overview

In this study, we build on our earlier modeling work and upon previous renewable integration studies to estimate how locations of PV systems affect the need for reserves in future power systems. We use California's long-term planning process as a case study, modeling the need for reserves when load, wind and solar are fixed at levels that are expected to meet the state's 33% by 2020 goals: 12 GW of photovoltaics and 9.5 GW of wind (Energy and Environmental Economics (E3), 2014). We then vary the locations of PV systems to compare centralized versus distributed arrangements, centralized versus distributed balancing authorities, and regional climates. In doing so, we answer the question of how much geographic dispersion of PV systems can mitigate flexibility need in a realistic future power systems.

In addition to quantifying reserve needs, we also estimate of the energy production and capacity value of solar generation in these different scenarios. In doing so we explore trade-offs between siting PV systems to minimize reserves, or to maximize energy production or capacity value.