Poster Abstract: Estimating Behind-the-meter Solar Generation with Existing Measurement Infrastructure

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ABSTRACT

Real-time PV generation information is crucial for distribution system operations, in particular for switching operations, state-estimation, and management of the voltage at the point of provision. However, most behind-the-meter solar installations are not monitored. Typically, the only information available to the distribution system operator is the installed capacity. Our main purpose in this study is to estimate behind-the-meter PV generation using data from smart meters.

1. INTRODUCTION

The distribution system is facing a fundamental shift. Behind-the-meter distributed energy resources (DERs) may have significant implications for real-time operations of the distribution system. But often, distribution system operators do not have the necessary visibility into DER availability, flexibility or consumption/generation patterns.

The location of loads and generation within a distribution network plays a crucial role [1]. The effect of PV generation on feeder operations vary widely, and can be either positive or negative depending on feeder topology, climate, and the timing of other connected loads [2, 3]. Furthermore, [3] shows that using similar profiles for PV generation at different nodes overestimates voltage control actions.

The current state-of-the-art for modeling PV generation are (i) model-based approaches based on PV array geometry and irradiance measurements [4], and (ii) direct measurement of the real-time generation. Both methods have drawbacks. Monitoring each PV system is expensive and may not capture consumers who installed solar without proper permitting. Modeling PV, on the other hand, requires accu-

Figure 1: Data updates and estimation framework

rate knowledge of where PV systems are in the system, and their geometries. Furthermore, research suggests that these models can be inaccurate [5].

In this paper, we present a proof-of-concept method for estimating the PV generation at each household on a distribution feeder using only AMI data. This method provides visibility into where PV are located in the distribution system, the rated capacity of PV systems, as well as their production. We envision this work contributing toward a new framework for monitoring and control of DER in distributions systems, shown in Figure 1. In this framework, models will train on spatially rich data that is obtained with delay—such as AMI data. These models are designed so that they can be applied to data that are available in real-time but aggregated, such as those from supervisory control and data acquisition systems (SCADA) and weather stations.

2. METHOD

Previously, we developed a methodology to estimate PV generation at the feeder level using measurements from microsynchrophasors [6]. In this paper, we expand this methodology by disaggregating PV generation at the individual household level by adding the AMI data information as a constraint. Furthermore, since the reactive power measurements are unavailable, we are using hourly temperature data to model aggregate loads at the distribution feeder level.

We suggest the following learning and estimation strategy. At any given point in time t , we define the net load at the substation as NL_t , the aggregate load as AL_t , and individual solar generation S_t^i for each household i . We also define an irradiance proxy measurement as ϕ_t .¹ We assume there

¹The irradiance proxy could be from any number of sources.

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Figure 2: Solar disaggregation results

are N households with solar generation and we define the customer load at each household i time t as L_t^i . We model the solar generation S_t^i using the irradiance proxy measurement ϕ_t . Furthermore, we assume we have individual AMI measurement at the customer level such that

$$L_t^i + S_t^i = AMI_t^i. \quad (1)$$

Next, we define the aggregate load at the substation as AL_t . For simplicity in notation, we assume there are also N households with load (i.e. there is no house without PV generation) and model the aggregate load as a function of outside temperature $f(T_t)$. Specifically, we model the temperature effects on load as piecewise linear as shown in [7]. We use the complete set of measurements and can cast the following contextually supervised source separation problem:

$$\begin{aligned} & \underset{AL_t, L_t^i, S_t^i, C_{eff}^i, \Theta}{\text{minimize}} && \{\alpha(AL_t - \Theta f(T_t))^2 + \beta \sum_i^N (S_t^i - C_{eff}^i \phi_t)^2\} \\ & \text{subject to} && L_t^i + S_t^i = AMI_t^i \\ & && \sum_{i=1}^N L_t^i = AL_t \end{aligned} \quad (2)$$

For the purposes of this initial investigation we used 2 days' data from 10 houses monitored by Pecan Street Inc. [8]. Pecan street sub-meters PV generation and load within the homes at a rate of 1 min^{-1} . All houses are located in Austin, TX, and Pecan Street also provides hourly weather data for the time period that the homes are monitored.

3. RESULTS

Figure 2 shows actual versus disaggregated PV energy production from three households in the dataset. We observe that the proposed method works well for the homes with solar but not for the home without (ID# 1508), which estimates a small amount of PV generation when in fact there is none. In future work we suggest improving the methodology by adding an ℓ_1 regularization term for all values of C_{eff} which will induce sparsity.

The disaggregation method is also able to recover otherwise unknown dynamics in load, shown in Figure 3. Load exhibits erratic behavior in all homes: ID# 1283 exhibits what looks like duty cycling, and ID #1800 exhibits large variability in the first half of the day but not during the second half. In both cases, the disaggregation method is able to recover this variability though there are no regressors in the linear model that might capture it.

E.g., a monitored PV generation unit nearby, irradiance measurements from a weather station, or estimated irradiance from satellite observations

Figure 3: Load disaggregation results

4. DISCUSSION

In this paper, we disaggregate PV generation at individual households from historical AMI data. However AMI data are typically only available the day after collection, too late to be used in distribution system control. We plan to expand this work by conditioning our models on SCADA and weather data that are available in real time. We will then design the model to train on AMI data, but run in real-time to disaggregate PV generation and load from each home using only weather and SCADA data. This information is necessary for actively controlling distribution system equipment to prevent the adverse impacts of distributed PV, such as voltage violations and reverse power flow.

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