NASPI Distribution Task Team Technical Report

NASPI DisTT Use Case: DG-Load Disaggregation

April 25, 2017

Use Case

Disaggregation of net metered distributed generation (DG) from customer load uses high-precision measurements on the utility side of the meter to estimate the actual generation and amount of load offset behind the meter.

Background

When the distribution utility lacks access to separate load and generation telemetry from customer premises, net metered solar generation masks an unknown amount of load. This masked load implies a greater system exposure to contingencies. The masked load must be accounted for to assure adequate generation reserves in case of simultaneous tripping of many DG units, and to assure safe cold load pickup after an outage.

Innovative algorithms combine microsynchrophasor measurement unit (µPMU) measurements on the utility side with available solar irradiance data for a high-fidelity estimate of individual PV generation and masked load, even when not directly metered.

The conventional approach to estimating DG output is based on reported generation capacity, irradiance data, and generalized solar production models. These models lack specific information about operational up-time or degradation of any given PV installation, and their fidelity suffers during variable (non-clear-sky) conditions, which are precisely those of greatest interest. Alternative approaches to identifying actual DG output and masked load include adding telemetry on customer premises, or accessing customer PV generation data by way of third-party online platforms; each of these have intrinsic technical and non-technical challenges.

Examples

Algorithms for DG-load disaggregation have been developed and tested in the context of experimental field deployments of µPMUs at Riverside Public Utilities. In the case illustrated in Figure 1, direct measurements from a 7-MW PV array were available for comparison and algorithm validation. The best estimation algorithm, using a combination of linear regression and machine learning techniques, agreed with direct measurements to within better than 6% (RSME) over a range of conditions. [1], [2]

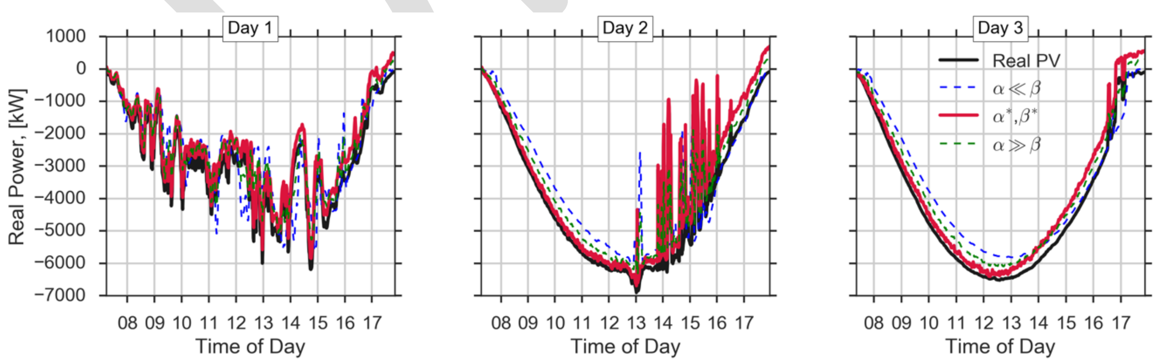

Figure 1 Experimental validation of DG-load disaggregation algorithm on a high-pen solar circuit. The graphs show PV generation measured (black) and estimated (red and dashed lines) with variations of an algorithm that uses µPMU measurements of aggregate voltage and current at the substation, along with irradiance data. The α and β parameters are weighting factors that systematically attribute errors to the linearized representation of load and PV as a function of their volatility. LBNL.

Expected future examples will provide disaggregation of larger numbers of DG units on residential and small commercial circuits.

In addition to revealing masked load, visibility of short-term DG behavior from the utility side of the meter will provide the potential benefits of validating smart inverter performance and correlating PV generation with feeder conditions such as voltage profile.

Data Requirements

DG-load disaggregation draws on continuous high-resolution time-series measurements of voltage and current, including local current vs. voltage phase angle for displacement power factor, from a single measurement point. There is no critical threshold for sampling rates or absolute accuracy; the fidelity of the estimate will improve in direct relation to data quality. Extant algorithms successfully used µPMU data with 120Hz sampling and accuracy constrained by revenue-grade instrument transformers. This use case does not require comparative voltage phase angle measurements between locations. Future analytics might be enhanced by algorithms that use simultaneous power quality measurements in the time domain to identify harmonic signatures.

Development and Limitations

Tools and algorithms for this use case are at Technology Readiness Level (TRL) 6, ready for deployment in pilot-scale demonstrations. Opportunities exist for further refinement of disaggregation algorithms.

References

[1] E. Stewart, C. Roberts, A. Liao, A. von Meier, O. Ardakanian, K. Brady, and A. McEachern, “Predictive distribution component health monitoring with distribution phasor measurement units,” Submitted for publication to: Transactions Smart Grid 2016.

[2] Lawrence Berkeley National Lab. [Online]. Available: https: //eventdetect.lbl.gov