Real-Time Regional PV Spinning Reserve Estimator with AGC Look-Ahead Windows

Preprint

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National Renewable Energy Laboratory

Presented at the 50th IEEE Photovoltaic Specialists Conference
San Juan, Puerto Rico
June 11-16, 2023

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Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00-85148
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Suggested Citation
Cai, Mengmeng, Govind Saraswat, and Vahan Gevorgian. 2023. *Real-Time Regional PV Spinning Reserve Estimator with AGC Look-Ahead Windows: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-85148.
https://www.nrel.gov/docs/fy23osti/85148.pdf.

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Real-time Regional PV Spinning Reserve Estimator with AGC Look-ahead Windows

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***Abstract*—Curtailed PV generation is a zero-marginal cost spinning reserve that can be used for a number of active power control services. However, unlike the traditional spinning reserve providers, i.e., fossil-fueled generators, who have well-defined operating characteristics, e.g., available headroom or potential high limit (PHL), PV plants have by nature variable and uncertain operating characteristics. To ensure the effective coordination between PV plants and the system operator during an active power control event, accurate forecasts of the PV PHL are essential. A novel reference-control grouping based scaling method has been proposed by NREL to estimate the PV PHL in real-time. This work further enhances the methodology by: 1) improving the model accuracy through machine learning; 2) considering look-ahead windows introduced by the computation and communication latencies; 3) applying the method to regional spinning reserve estimation. A significant performance improvement, around 2% less time when the estimation error falls below 1% of the capacity, has been observed based on real-world data collected by CAISO and PV plant operators.**

Keywords*—*PV, Spinning Reserves, Reliability Services, Potential High Limit

I. INTRODUCTION

The integration of variable energy resources (VERs) is gaining momentum in the U.S., adding great variability and uncertainty to the bulk power system. More system flexibilities from various energy resources are therefore needed to maintain the system reliability, including flexibility coming from the wind and solar plants themselves [1]. To resolve the emerging need, California independent system operator (CAISO) recommended the active power control of VERs, by which the VERs operate at curtailed generation points following automated dispatch instructions in response to a grid service need. Several demonstration projects conducted in Texas, Puerto Rico, and California under the collaboration between the U.S. Department of Energy (DOE) and industry have proven the capability of utility-scale PV plants in providing a full spectrum of reliability services, i.e., primary frequency response, automatic generation control, inertial response and ramp control, etc., as opposed to being just a source of variable bulk energy production [2], [3].

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This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government.

However, unlike the traditional operating reserve providers - fossil-fueled generators - who have well-defined operating characteristics, e.g., available operation headroom, PV plants by nature have variable and uncertain operating characteristics. To ensure an optimal and feasible coordination between PV plants and system operator during an active power control event, it is important to accurately estimate the potential maximum available power output, or potential high limit (PHL), of the plant at any moment even when the plant is curtailed to a lower production level. The PHL is driven by the solar irradiation and the plant condition [4] and therefore varies across time and cannot be measured directly. Estimating the PV plant PHL in curtailed mode is not a trivial task, especially for large PV plants spanning large geographical spaces. Both model-based and data-driven methods have been proposed for the PV plant PHL estimation [5]–[8]. However, all of them are highly dependent on accurate knowledge of plant-level and device-level parameters as well as the weather conditions. A simpler and potentially more accurate method has been developed by NREL that uses only a subset of inverters (control group) to achieve desired levels of curtailment and uses the other uncurtailed subset of inverters (reference group) to estimate the plant-level PHL in real-time. This method demonstrates superior performance compared to the ones found in the literature given its robustness, simplicity, and independence of PV modules, inverter types, array topology, solar irradiance variation, cloud movements, panel temperatures, and panel soiling, etc. Its real-world application has been shown in [3] under clear-sky days for a single 300 MW PV plant in California. Full detail of the NREL method can be found in [9].

In this work, NREL further enhances the methodology by:

1) Improving the estimation accuracy through machine learning (ML).
2) Accounting for look-ahead windows to reflect the computation and communication latencies occurring during the implement of the active power control.
3) Applying it for the regional reserve estimation.

II. METHODOLOGY

The NREL PV PHL estimation approach is enabled by splitting inverters in a PV plant into a control group and a reference group. While inverters in the control group are curtailed to track with the dispatch instructions, inverters in the reference group are reserved to operate at their maximum operating limits. Fig. 1 illustrates how the group splitting and PHL estimator fit into the PV plant active power control application, taking the automatic generation control (AGC) as the example.

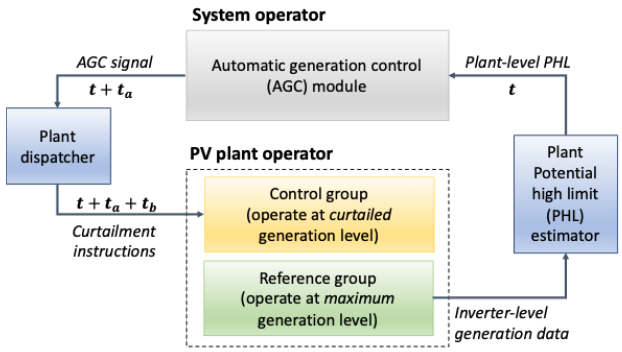

Fig. 1. Illustration of the automatic generation control enabled by the control-reference grouping and PHL estimation.

As depicted in Fig. 1, the plant PHL estimator first collects inverter-level generation data from the reference group and estimates the plant-level PHL to be sent to the system operator at time t. Then, the system operator calculates the optimal AGC signals for all participating generators, including the PV plant, based on their available headroom and response speed, which are communicated back to the plant dispatcher at time $t + t_a$. Finally, after receiving the AGC signal, the plant dispatcher determines the PV curtailment instructions at the inverter-level for the control group and executes the controls at time $t + t_a + t_b$.

Note that t_a and t_b reflect the computation and communication delays occurring in the AGC control loop. Since PV is a variable generation, the actual available power of the plant at time interval $t + t_a + t_b$ could differ from the estimated available power at t if no look-ahead window is considered, which will increase the estimation error. In what follows, we compare two mathematical models for estimating the PHL: 1) the scaling model, originally proposed in [9], that is incapable of considering the look-ahead window, and 2) the proposed ML model, introduced in this study, with configurable look-ahead windows.

A. Scaling Method

The scaling method simply estimates the plant-level PHL at time $t + t_a + t_b$ as a scaled value of the reference-group PV generation at time t, based on the ratio between numbers of inverters in the reference group versus in the PV plant, as given in Eq. (1):

$$\hat{P}_{PHL}^{t+t_a+t_b} = \frac{N}{N_{ref}} \sum_{k=1}^{N_{ref}} P_{ref}^{t,k}, \tag{1}$$

where N and N_{ref} indicate the numbers of inverters in the plant and the reference group. $P_{ref}^{t,k}$ represents the measured power output of reference inverter k at time t.

B. Machine Learning Method

Despite the fact that the scaling method has been successfully demonstrated and used in a number of projects, it has two drawbacks: First, same weights are assumed for inverters in the reference group when estimating the plant-level PHL, whereas varying weights may actually apply given different modules, capacities, and locations of the reference inverters. Second, the scaling method does not have any foresight, given that it by default assumes an equal relationship between generations at two separate time steps. To address the above-mentioned gaps, a linear regression based PHL estimation model, $f(\cdot)$, is introduced. As stated in Eq. (2), given a linear model $f(\cdot)$ whose coefficients are trained based on historical data, the estimated plant-level PHL at time $t + t_a + t_b$, $\hat{P}_{PHL}^{t+t_a+t_b}$, can be computed as a weighted linear combination of reference inverter generations at time t, $\mathbf{P}_{\mathbf{ref}}^{\mathbf{t}}$, and two time indexes corresponding to the forecasting time t, TI^t, and execution time $t + t_a + t_b$, $TI^{t+t_a+t_b}$.

$$\hat{P}_{PHL}^{t+t_a+t_b} = f(\mathbf{P}_{\mathbf{ref}}^{\mathbf{t}}, TI^t, TI^{t+t_a+t_b}) \tag{2}$$

Note that the time index, TI, is innovatively introduced in our study to capture the variation of the clear-sky generation across time, which is unique to each plant given its geographical location and tracking technique being applied. The intuition behind is that the ratio between all-sky generation and clear-sky generation (caused by the cloud cover) should keep relatively constant in near term as the cloud condition won't change drastically for a matter of seconds. Such that, by taking the two time indexes into account, the model can capture the trend of generation growth/drop between two time steps. It is designed as a normalized upper envelope of PV generation profiles collected from recent historical days, as exampled in Fig. 2.

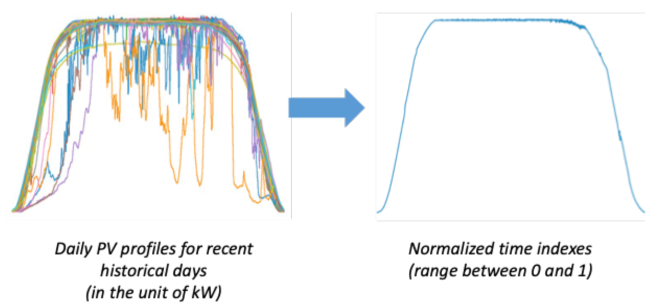

Fig. 2. Illustration of the time indexing.

C. Regional Estimation

Once the estimated plant-level PHLs for PV plants located in the same balancing authority are obtained, the regional PHL can be estimated by simply summing the plant-level values up, as given in Eq. (3), assuming M PV plants are in the region.

$$\hat{P}_{PHL,regional}^{t+t_a+t_b} = \sum_{m=1}^{M} \hat{P}_{PHL,m}^{t+t_a+t_b} \tag{3}$$

III. Case Study

A. Dataset

A case study is performed applying a month-length high-bandwidth inverter-level dataset, collected by 4 utility-scale PV plants in California, to evaluate the performance of the proposed PHL estimator. All data were cleaned and interpolated to one-second resolution. In addition, CAISO provided plant-level production and curtailment set points data covering the

TABLE I. Frequency when the estimation error falls between +/-1% of capacity under varying look-ahead windows

Percentage of time	ML-based approach	Scaling-based approach
0 AGC step	99.30%	97.79%
1 AGC step	99.16%	97.65%
2 AGC steps	98.93%	97.32%
3 AGC steps	98.58%	97.00%

same month at 15-min interval to help identify periods with curtailments. 25 out of the 31 days' data are picked out after a quality check. And we further split the 25 days' data into the training and testing datasets based on a 7:3 ratio. One linear regression model is created for each PV plant for a particular length of look-ahead window.

B. Performance Evaluation

Fig. 3 depicts the histograms of percentage errors (with respect to the plant rated power) for four plants with 0-3 AGC steps (0-12s) look-ahead windows, obtained by the proposed ML-based method. It is noted that the percentage errors are symmetrically centered around zero. For over 96% of time, the estimation errors are below 1% of the rated power for all four plants. Moreover, trivial performance drops are observed as the look-ahead window grows.

Table. I compares the regional estimation performance between the scaling-based and the ML-based methods, using percentage of time When the estimation error falls between +/-1% of the capacity as the performance metric. It is shown that the ML-based approach provides a significant improvement in regional spinning reserve estimation compared to the scaling-based method at all three AGC intervals.

IV. Conclusion

A ML-based model is proposed to further enhance the control-reference grouping based PHL estimation approach developed at NREL. It demonstrates superior performance compared with the original scaling-based model given real-world data collected by CAISO and PV plant owners.

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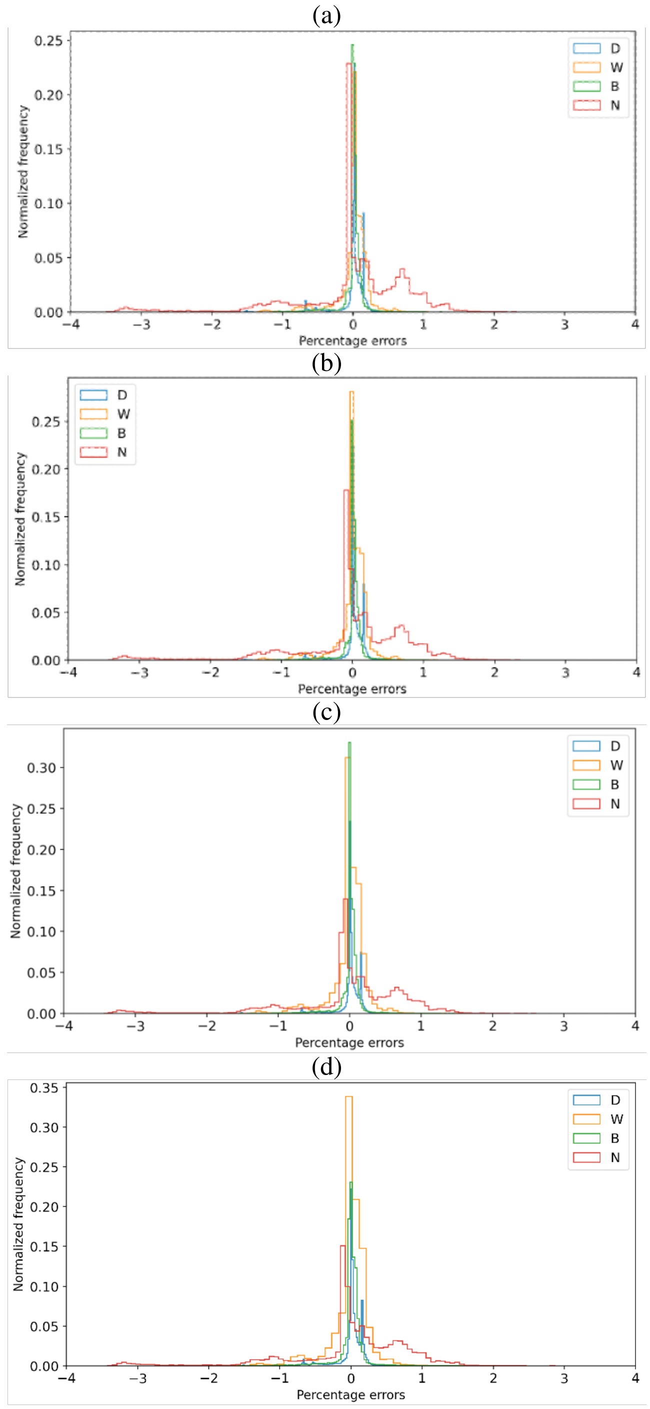

Fig. 3. Histograms of plant-level percentage errors for (a) 0, (b) 1, (c) 2, and (d) 3 AGC steps ahead (D, W, B, N represents IDs of the four plants)

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