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Detection and Analyze of Off-Maximum Power Points of PV Systems based on PV-Pro Modelling

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***Abstract* — Photovoltaic (PV) systems can operate off the maximum power point (MPP) for various reasons. Understanding when off-MPP behavior occurs is essential to the maintenance and operation (O&M) of PV systems. To detect off-MPP data, a reference power is usually needed, which can be obtained by system modeling that generally relies on physical model parameters. Traditional methods commonly obtain these parameters based on the initial condition of the PV system such as from the module datasheet. However, these parameters often do not reflect the current condition of the on-site PV system, which is likely to suffer from degradation and faults after years of operation with degraded parameters. Thus, we propose an off-MPP analysis algorithm based on the PV-Pro method, which can extract the model parameters (like series and shunt resistance) at the current operating condition only using the routine production data. In this way, the system power, current, and voltage can be accurately modeled. The off-MPP points are detected by comparing the measured power with the one modeled by PV-Pro. Points with large disagreement in power are further analyzed by deconvolving it into the error of the current and voltage at MPP, which allows tracing the error source of the off-MPP and provides valuable information for the O&M of PV systems. This off-MPP analysis is demonstrated on a 271kW PV field system, where it is shown that most of the off-MPP points are caused by the reduced DC current.**

I. INTRODUCTION

To detect anomalies in the output power of a PV system, a reference value of power is generally needed, which can be obtained via system modeling [1]. To perform PV system modeling, the equivalent model parameters are essential [2]. Traditional methods often estimate the model parameters based on the initial status of the PV module, such as from the manufacturer data sheets [3]. However, these model parameters do not reflect the actual status of an on-site PV system, which may suffer from degradation and various faults after years of field operation [4].

This paper presents a detection method for off-maximum power point (MPP) data based on accurate modeling of the PV system including model parameter estimation. The modeling is conducted by a methodology named PV-Pro [5] from our previous research. It can estimate the model parameters at the current operating condition using only the routine operation data. Thus, PV-Pro allows us to precisely model the output power, current, and voltage to perform the off-MPP analysis.

The remainder of the paper is organized as follows: Section II introduces the off-MPP algorithm. Section III demonstrates the algorithm on a field PV system. Results are discussed in Section IV. Section V concludes the paper.

II. METHODOLOGY

The proposed off-MPP algorithm consists of three steps, as depicted in Fig. 1. The first step is to estimate the operation data (P_{mp}, V_{mp}, and I_{mp}) using the model parameters extracted by PV-Pro. The next step is to classify data points as off-MPP when the P_{mp} error exceeds a predetermined threshold. The final step is to deconvolve the P_{mp} error based on analyzing the V_{mp} and I_{mp} error to trace the root cause.

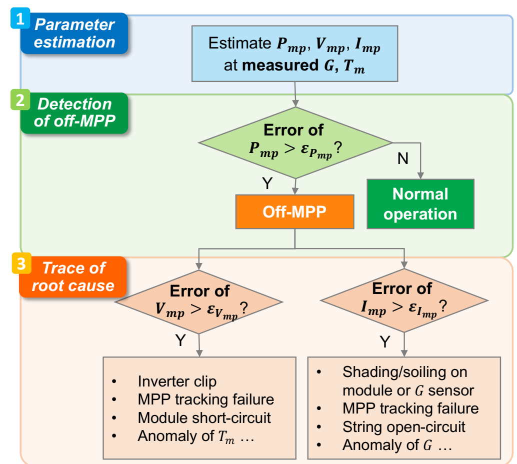

Fig. 1 Pipeline of three-step off-MPP analysis.

A. Estimation of operation data using PV-Pro

PV-Pro [5] is a methodology to extract the PV equivalent model parameters at the current operating condition from routine PV production data and environmental data (irradiance G and module temperature T_m). Extending the Suns-Vmp method [6], PV-Pro extracts the five single-diode model (SDM) parameters, allowing the PV system to be modeled under any environmental condition. It should be noted that the SDM parameters extracted by PV-Pro reflect the actual condition of the PV system, including degradation or faults. This makes the subsequent PV system performance modeling much more accurate compared to the methods that leverage the SDM parameters extracted from the module datasheet [3]. An example of the estimated P_{mp} of one field PV system [7] using the initial (via NREL PyPVRPM model [8] based on the datasheet) and PV-Pro- extracted SDM parameters is plotted in Fig. 2. It is shown that after years of operation, the P_{mp} estimated using initial parameters can no longer fit the measured one. In contrast, the P_{mp} obtained by PV-Pro still well models the system performance. Thus, off-MPP analysis based on PV-Pro modeling will be more resistant to changes in system parameters over time.

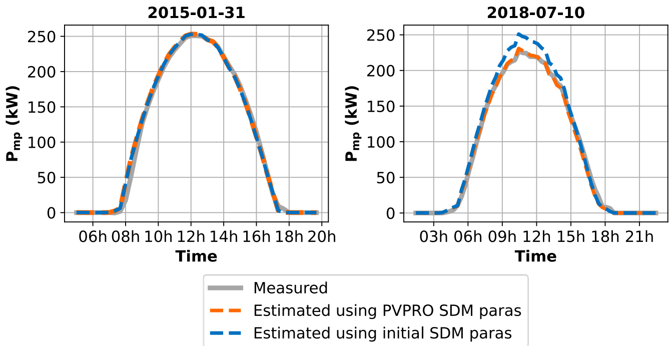

Fig. 2 Estimated P_{mp} of NIST ground array (began operation in 2015) using initial and PV-Pro-extracted SDM parameters at two different times. After three years of operation, the estimated P_{mp} using initial SDM parameters does not fit the measured one, while the P_{mp} modeled using PV-Pro still matches well.

In this study, based on the SDM parameters extracted by PV-Pro, P_{mp}, V_{mp}, and I_{mp} are estimated at the measured G and T_m for the off-MPP analysis.

B. Detection of off-MPP

To detect off-MPP points, the threshold method is adopted, *i.e.*, when the error of power (ε_P) exceeds a pre-determined threshold, the data point will be identified as off-MPP. As the system power varies with the irradiance and temperature, we set the threshold as a ratio to the estimated power. The default value is 10%. It can be customized based on the specific requirements of the user on the off-MPP detection sensitivity.

C. Analysis of off-MPP

Because the DC power is the product of DC voltage and current ($P = VI$), after detecting the off-MPP points, it is also necessary to find out where the error of power comes from and quantify the contribution of each factor. First, the error of voltage (ε_V) and current (ε_I) are calculated based on the V_{mp} and I_{mp} estimated by PV-Pro. Then, the power error caused by voltage or current error is calculated independently, as presented in (2-3).

$$\varepsilon_{P_{\varepsilon_V}} = P - P_{\varepsilon_V} = V \cdot I - (V - \varepsilon_V) \cdot I = \varepsilon_V \cdot I \qquad (1)$$

$$\varepsilon_{P_{\varepsilon_I}} = P - P_{\varepsilon_I} = V \cdot I - V \cdot (I - \varepsilon_I) = V \cdot \varepsilon_I \qquad (2)$$

Next, the power error when both voltage and current error exist ($\varepsilon_{P_{\varepsilon_V \varepsilon_I}}$) is also calculated:

$$\begin{aligned}\varepsilon_{P_{\varepsilon_V \varepsilon_I}} &= P - P_{\varepsilon_V \varepsilon_I} = V \cdot I - (V - \varepsilon_V)(I - \varepsilon_I) \\ &= V \cdot \varepsilon_I + \varepsilon_V \cdot I - \varepsilon_V \cdot \varepsilon_I \end{aligned} \qquad (3)$$

Using $\varepsilon_{P_{\varepsilon_V}}$, $\varepsilon_{P_{\varepsilon_I}}$, and $\varepsilon_{P_{\varepsilon_V \varepsilon_I}}$, we define the contribution of the voltage and current error to the final power error (namely C_V, C_I) as expressed in (4-5).

$$C_V = \frac{\varepsilon_{P_{\varepsilon_V}}}{\varepsilon_{P_{\varepsilon_V \varepsilon_I}}} = \frac{\varepsilon_V \cdot I}{V \cdot \varepsilon_I + \varepsilon_V \cdot I - \varepsilon_V \cdot \varepsilon_I} \qquad (4)$$

$$C_I = \frac{\varepsilon_{P_{\varepsilon_I}}}{\varepsilon_{P_{\varepsilon_V \varepsilon_I}}} = \frac{V \cdot \varepsilon_I}{V \cdot \varepsilon_I + \varepsilon_V \cdot I - \varepsilon_V \cdot \varepsilon_I} \qquad (5)$$

It may be noted that the sum of C_V and C_I does not equal unity. This is because two factors (V and I) simultaneously impact the power. Thus, the ε_P when both factors act is not a simple sum of the ε_P when only one factor acts. Nevertheless, C_V and C_I reflect the relative contribution of the voltage and current error to the final power error.

III. Case study of a 271kW PV field system

This section presents a demonstration of the proposed off-MPP analysis on a field PV system, *i.e.*, the NIST ground array [7]. The array is located in Gaithersburg, Maryland, USA. It is ground mounted with a fixed tilt angle of 20°. 1152 modules (Sharp NU-U235F2, 235W, sc-Si) are installed, yielding 271 kW output. Data from 2015 to 2019 are available for analysis.

PV-Pro is applied to extract the SDM parameters based on every 2-week operation data over the 4-year data. Using these extracted parameters, the V_{DC} and I_{DC} are estimated and compared with measured values. The average relative error is less than 1%, which shows the overall good modeling capability of PV-Pro.

Next, the off-MPP points are detected. The P_{mp} error (*i.e.*, difference in modeled and observed P_{mp}) of the NIST ground array is plotted in Fig. 3. It is shown that, when the threshold is 10% of the estimated power, the off-MPP ratio is 4.93% over the 4-year operation time.

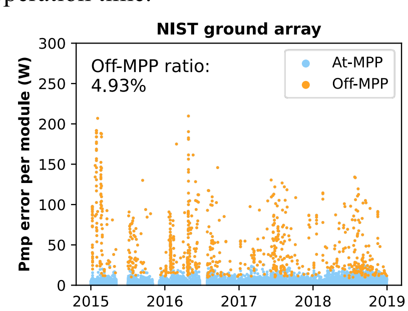

Fig. 3 P_{mp} error (per module) of the NIST ground array. PV-Pro identifies the presence of off-MPP in 4.93% of the operation time.

To further analyze these off-MPP data, the relative error (RE) of V_{mp} and I_{mp} is calculated and plotted in Fig. 4. We note that the relative error of V_{mp} varies in [0, 20%] while that of I_{mp} is much higher with the value in [0, 100%].

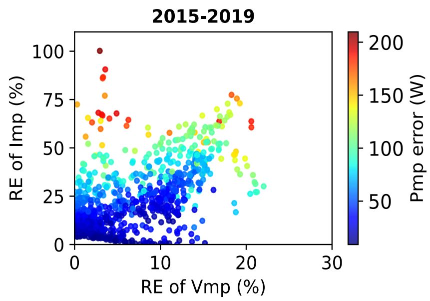

Fig. 4 Distribution of off-MPP points of the NIST ground array 2015-2019. The RE of I_{mp} varies more intensely than that of V_{mp}.

To quantify the contribution of the error of V_{mp} and I_{mp} to the P_{mp} error, Step 3 of the algorithm is performed. To illustrate, one day of the off-MPP data (Fig. 5 (a)) is selected as an example. Using (4) & (5), the contribution of the error of V_{mp} and I_{mp} is calculated and presented in Fig. 5 (b).

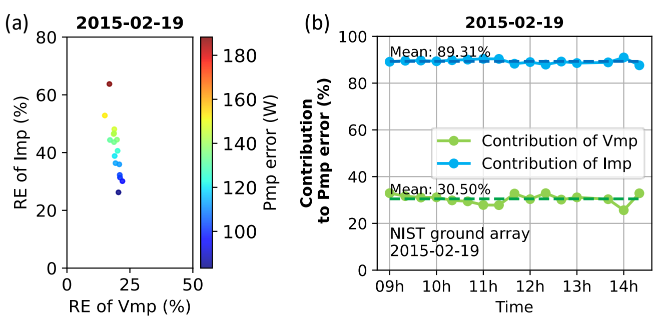

Fig. 5 (a) Relative error of V_{mp} and I_{mp} of one off-MPP cluster (b) Contribution of V_{mp} and I_{mp} error to P_{mp} error. The results show that I_{mp} error contributes more to the P_{mp} error on 2015-02-19.

It is revealed in Fig. 5 that, on 2015-02-19, although the relative error of I_{mp} varies from 25% to 65%, its contribution to the P_{mp} error (Fig. 5 (b)) is relatively stable and higher (89.3%) than that of V_{mp} (30.5%). This indicates that the I_{mp} error is the primary source of the off-MPP operation and proper O&M strategies to mitigate off-MP can focus on factors impacting the current generation, like shading, soiling, or module short-circuit.

IV. Discussion

The core part of the off-MPP algorithm is the modeling using PV-Pro, which allows extracting the SDM parameters reflecting the current condition of the PV system based on the historical operation data. Therefore, this off-MPP algorithm is promising for application to real-time health monitoring of PV systems as accurate performance modeling is made possible by PV-Pro. This will also be the focus of future research.

V. Conclusion

This paper presents an off-MPP detection and analysis algorithm, which is based on accurate modeling of the current operating performance of the PV system using PV-Pro. The detected off-MPP are analyzed by quantifying the contribution of each error source (from current or voltage). This algorithm is demonstrated on a field PV system where the modeling error is below 1%. It is revealed that the primary source of the off-MPP is a decrease of current, which points out a clear direction for the planning of O&M for the PV system. The PV-Pro with the off-MPP algorithm is available on Github: https://github.com/DuraMAT/pvpro

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