Degradation analysis of photovoltaic modules based on operational data: effects of seasonal pattern and sensor drifting

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Abstract. Degradation analysis of photovoltaic (PV) modules based on real operational data is essential to the future development of the PV industry. Weather conditions and system drifting often lead to large uncontrollable fluctuations in operational data, which present great challenges for calculating degradation rates of PV modules. In this paper, we propose a new numerical two-step approach to overcome these difficulties. In particular, we will show that our method is able to eliminate effects of seasonal patterns and systematic sensor drifting in evaluating degradation rates of PV modules. The method is applied to the six-year operational data of a solar PV system installed at CA United States. We demonstrate that our approach can greatly improve the degradation calculations, compared with other widely used methods.

1. Introduction

The performance degradation of photovoltaic (PV) modules is one of the key factors that limit the future development of the PV industry. The degradation of modules is the main reason for the power output loss of PV systems over time. Reducing the module degradation rates is therefore technically essential for the purpose of improving the energy efficiency of solar PV systems. Because PV modules are usually guaranteed for more than 20 years by manufacturers, it is also important for financial reasons to track and control the long-term degradation of PV modules. It has been well known that the degradation of individual modules (in long or short term) can be attributed to the intrinsic properties change of the PV materials caused by either external potential --- potential induced degradation (PID) [1], or the light --- light induced degradation (LID) [2]. Since the module always operates in a system, some other mechanism external to the solar cells such as interconnect issues and solder bonds could also play a significant role in the performance degradation, which makes it necessary to determine the degradation rates under operation conditions instead of indoor testing of isolated modules. Consequently, a reliable numerical method for degradation analysis of real operational data is of great importance for not only the fundamental research but also the future development of the PV industry.

There are two major difficulties in evaluating degradation rates of PV modules from real operational data. One is the large fluctuations of the operational data due to uncontrollable external parameters such as weather conditions (raining, clouds movement, etc.) and unexpected changes of factors external to PV systems (unexpected shading, inverter problems, etc.). The other one is the
systematic ‘degradation’ in real operational data caused by the commonly existing seasonal patterns and/or the sensor drifting (for example, the drifting of irradiance sensors) instead of PV modules. The first problem has been intensively discussed. Many numerical filtering techniques that help people to effectively extract useful information from real operational data with large uncontrollable fluctuations have been proposed and widely used in degradation analysis of PV systems [3-10], a nice example of which can be found in Ref. 3. On the contrary, the second problem (caused by seasonal pattern and/or sensor drifting) has been rarely discussed in literature. It has been well known that energy output of PV systems sensitively depends on weather conditions [11] [37], but the seasonal patterns that often occurred in operational data have not been seriously considered in degradation analysis yet. Sensors are important parts of PV systems [12-19]. The sensor drifting is an inevitable issue in assessing the performance of systems. From a simple estimation, we can see how significant the sensor drifting could be for the degradation analysis of PV systems: The degradation rate of silicon based PV modules typically is around -0.7% per year [11], and the performance ‘degradation’ caused by sensor drifting could be easily more than -2% per year [20]. In this paper, we suggest a two-step approach (TSA) that takes into account effects of seasonal patterns and sensor drifting. From our calculations based on 6-year operational data of a PV system in California, we show that our TSA (together with the effective filtering techniques [3]) is able to significantly improve the quality of degradation analysis of PV systems, providing a reliable numerical tool for tracking module degradation for the PV industry.

2. Data collection and initial processing
The concrete roof top mounted system under study was installed at Chowchilla, CA, United States. Up to 1736 multi-crystalline solar PV modules were used with the peak power of 220W for each of them. After the commissioning of both the solar PV system and a weather station nearby (used for recording weather data), 6-year data (both solar power and weather data) is available from January 1st 2009 to December 31st 2014. In order to minimize the inverter effects, here we only present our analysis of DC data. Before the degradation analysis, the original data was filtered by irradiance limits, stability, and outlier filters to eliminate the uncertainty originated from uncontrollable fluctuations due to weather conditions, shading and system interrupts [3]. In figure 1, we show the filtered power and irradiance data. These data are used for the degradation analysis that will be discussed later. A periodic seasonal pattern can be clearly seen in both power and irradiance data. The linear fitting of the irradiance data suggests that the irradiance sensor has a drifting rate of -1.0% per year, which will cause a significant ‘degradation’ in calculating performance of modules.
Figure 1. Filtered a) DC power of the solar system and b) irradiance data over 6 years.

The periodic seasonal pattern can be clearly seen in both figures. In b), the solid straight line is the linear fit of the irradiance data. The negative slope (-1.0% per year) of the line is caused by the drifting of the irradiance sensor.

3. Method and discussions
In conventional methods, the degradation rate of PV modules is obtained by linearly fitting either the performance ratio (PR) or the DC power of modules as a function of time. The linear fitting process eliminates the complicated periodic seasonal patterns in real operational data in a very simple manner. Also, the effects of the sensor drifting (Figure 1. b) are neglected, which may cause big problems as we shall see later. Currently, three different numerical methods of degradation analysis are widely used: 1) the PR-R\(_d\) method in which the degradation rate (R\(_d\)) is obtained by linearly fitting the PR as a function of time [7]. In this method, the PR is calculated by 
\[
PR = \frac{E_{output}}{H_{i}} \frac{P_0}{G_0} - 1
\]
where \(E_{output}\), \(H_{i}\) are the measured energy output of the modules and solar irradiation, respectively. Two constants, \(P_0\) and \(G_0\), are the nametag rating of solar systems and the peak value of irradiance; 2) the so-called DC/ G\(_{POA\text{-corr}}\) method [8] in which the degradation rate is calculated by linearly fitting the temperature corrected ratio of DC power over the irradiance as a function of time. The temperature corrected ratio (DC/G\(_{POA\text{-corr}}\)) is expressed as
\[
\frac{DC}{G_{POA\text{-corr}}} = \frac{Power_{DC}(T_{mod} - 25) + 0.43\% \cdot 1 \cdot P_0}{G_{POA} \cdot G_0}, \quad \text{where} \quad Power_{DC}\text{ is the measured DC power of solar systems, } G_{POA}\text{ is the plane-on-array irradiance, } T_{mod}\text{ is the module temperature, and } P_0, G_0\text{ are two normalized constants as before; 3) the regression PVUSA method [9] in which the parameter } R_d \text{ is computed by linearly fitting the DC power of the solar system as a function of time. In this method, the DC power is modeled as } P_{DC} = G_{POA} \cdot (A + B \cdot T_{amb} + C \cdot G_{POA} + D \cdot ws), \text{ where } T_{amb} \text{ is the ambient temperature, } ws \text{ is the wind speed, and } A, B, C, D \text{ are four regression constants derived from the operational data.}

We first apply the aforementioned three methods to the data shown in figure 1. The calculated PR or DC power and the linear fitting of them are shown in figure 2. The degradation rates obtained from these three calculations are +0.13%/year for the PR-R\(_d\) method, +0.84%/year for the DC/G\(_{POA\text{-corr}}\), and -1.39%/year for the PVUSA. Obviously, the previous two methods (PR-R\(_d\) and DC/G\(_{POA\text{-corr}}\)) give the wrong sign of R\(_d\), and the PVUSA greatly overestimate the degradation rate compared with the typical
The value of the degradation rate of silicon PV module (around -0.7% per year [11]). The problems of these three methods are caused by the neglect of significant irradiance sensor drifting effects (-1.0% per year for the system under study). For the PR-Rd and DC/GPOA_corr methods, the irradiance is in the denominator of the linearly fitted function, the neglect of the negative sensor drifting therefore leads to underestimated Rd, resulting in the wrong sign of Rd for the system under study. While, for the PVUSA method, the irradiance appears as a multiplier in the fitted function, causing an overestimated degradation rate.

\[ G_{POA} = G_{POA} \cdot (1 + \Delta \cdot Time) \]  

(1)

where \( G_{POA} \) is the measured irradiance and \( \Delta \) is the sensor drifting rate that can be determined by a linear fitting (figure 1b). For the system under study, \( \Delta \) is -1.0% per year. The corrected irradiance is then used in the second step to determine the degradation rate. The simple linear fitting in conventional methods is a rough approximation, which may miss some important information of the fitted function that in general has a periodic seasonal pattern. In light of this, we use a new model as following to fit the DC power (not linear fitting), from which \( R_d \) can be determined,

\[ P_{DC} = (R_d \cdot t + 1) \cdot (A \cdot T_{amb} + B \cdot G_{POA} + a_1 \cdot T_{amb}^2 + a_2 \cdot G_{POA}^2 + a_3 \cdot RH + a_4 \cdot ws + a_5) \]  

(2)

where \( P_{DC} \) is the fitted DC power, \( t \) is the time, RH is the relative humidity, \( A,B \) are initially set system parameters, and \( a_1 \) to \( a_5 \) are five constants that together with \( R_d \) can be determined by fitting \( P_{DC} \) to measured DC power. For current study, the humidity and wind speed are not available, so \( a_3, a_4 \) are set to zero.

**Figure 2.** Degradation rates demined from linearly fitted functions with three different methods: a) PR-Rd, b) DC/GPOA_corr and c) PVUSA. Blue dots are calculated functions from measured values, and solid lines are linear fitting.

In order to correctly take into account effects of the sensor drifting and also the seasonal pattern, we propose here a two-step approach for evaluating the degradation rate from real operational data. In the first step of the approach, the irradiance data is corrected by a linear time-varying factor so that the sensor-drifting effects can be eliminated. The corrected irradiance \( G_{POA} \) is calculated by the following equation,

\[ \bar{G}_{POA} = G_{POA} \cdot (1 + \Delta \cdot Time) \]  

where \( G_{POA} \) is the measured irradiance and \( \Delta \) is the sensor drifting rate that can be determined by a linear fitting (figure 1b). For the system under study, \( \Delta \) is -1.0% per year. The corrected irradiance is then used in the second step to determine the degradation rate. The simple linear fitting in conventional methods is a rough approximation, which may miss some important information of the fitted function that in general has a periodic seasonal pattern. In light of this, we use a new model as following to fit the DC power (not linear fitting), from which \( R_d \) can be determined,

\[ P_{DC} = (R_d \cdot t + 1) \cdot (A \cdot T_{amb} + B \cdot G_{POA} + a_1 \cdot T_{amb}^2 + a_2 \cdot G_{POA}^2 + a_3 \cdot RH + a_4 \cdot ws + a_5) \]  

where \( P_{DC} \) is the fitted DC power, \( t \) is the time, RH is the relative humidity, \( A,B \) are initially set system parameters, and \( a_1 \) to \( a_5 \) are five constants that together with \( R_d \) can be determined by fitting \( P_{DC} \) to measured DC power. For current study, the humidity and wind speed are not available, so \( a_3, a_4 \) are set to zero.
We now use the two-step approach to evaluate the degradation rate of the system under study. In figure 3, we show the fitted $\tilde{P}_{DC}$ (by the standard least square method) together with the measured DC power. Clearly, the fitted data nicely captured the periodic seasonal pattern of the measured ones. The $R_d$ is estimated to be -0.46\% per year by this method, which agrees nicely with previous experimental values of similar Si modules [11]. To separate the effects of seasonal pattern and the sensor drifting, we also tried to use the equation (2) with the original irradiance data (not the corrected one in equation (1)) to fit the DC power. By doing this, we neglect the sensor drifting and obtain an underestimated $R_d$ around 0.58\% per year as expected, which is also significantly different from aforementioned linear-fitting methods.

4. Conclusion

Season patterns and sensor drifting are two common issues in the operation of solar systems [11-32, ]. While, the effects of these two factors on degradation of PV systems are often neglected in conventional theoretical models [33-36]. In this paper, we proposed a two-step approach to numerically evaluate the performance degradation rate of PV systems from real operational data, which takes into account effects of seasonal patterns and irradiance sensor drifting. The method is applied to the 6-year data of a PV system installed in Chowchilla, CA, United States. Results from our two-step model are compared with those based on three other widely used methods. We show that together with existing effective filtering techniques, the two-step model is able to yield reasonable estimations of degradation rates of PV modules under operating conditions, providing a reliable numerical tool for tracking and analyzing the performance of PV systems.

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