Considering the Variability of Soiling in Long-Term PV Performance Forecasting

Preprint

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Considering the Variability of Soiling in Long-term PV Performance Forecasting

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***Abstract*—This study presents the development of a methodology for evaluating the variability associated with soiling on long-term PV forecasting. Independent engineering firms typically build P50 forecasts for large PV plants through the use of the PVsyst software, where monthly soiling losses are one of many inputs to the P50 model. Subsequently, long-term performance distributions, or Pvalues, are constructed through a Monte Carlo analysis that includes various factors such as: satellite irradiance modeling uncertainty, uncertainty in the PVsyst model, and long-term irradiance variability. Often the PVsyst model uncertainty is increased to account for sites with significant soiling concerns but no systematic method has been presented in the literature to specifically include soiling variability within Pvalues. In this work soiling information from 16 sites in the U.S. Southwest are combined with 20 years of rainfall data to generate 20 years of energy production with soiling losses and then subsequently generate Pvalues. The results show that the spread of Pvalues (P1-P99) can increase from 0-13% when interannual soiling variability is included.**

Keywords*—*photovoltaic soiling, performance forecasting, uncertainty, Pvalues, interannual variability

I. Introduction

Photovoltaic (PV) soiling loss is the well-known phenomenon where dust or other airborne particulates accumulate on the surface of PV modules causing light blockage and therefore power loss to the PV system. Soiling losses depend on local climate, geography, nearby pollution sources, module orientation and various other factors [1]. Annualized soiling losses can be as low as 0.5%/year in temperate climates with frequent rainfall and as high 30%/year in deserts such as the middle east [2, 3]. Revenue losses due to soiling losses depend on the specific PV system but can easily reach millions of dollars per year for large utility scale systems [4]. Independent Engineers (IEs) typically model utility scale PV system P50 performance (annual energy yield that expected to be exceeded 50% of the time) using PVsyst or other software where key inputs are satellite site irradiance, temperature, and wind speed, losses due to irradiance transposition to plane of array, PV module electrical parameters, various other electrical losses, and monthly soiling losses. These monthly soiling losses, specifically consideration for their interannual variability and a method to propagate this variability into the plant probabilistic performance (Pvalues) is the focus of this work. Monte Carlo simulations of annual plant energy yield are used to generate a P1 (1% of all observations are estimated to exceed this energy yield) and a P99 (99% of all observations are estimated to exceed this energy yield) among other Pvalues that might be desired. While there are various methods to generate PV system Pvalues, all methods generally include uncertainty of the satellite derived global horizontal irradiance (GHI), interannual variability of the weather (i.e. irradiance and temperature), and uncertainty in the PV power production model (i.e. uncertainties associated with irradiance transposition, electrical, availability, soiling, and other losses [5]. IEs typically have internal proprietary methods that have been developed through years of experience to assign an uncertainty distribution to each site-specific energy model. While soiling has traditionally been included as part of this overall model uncertainty, there has been sufficient progress in soiling research in recent years to consider an approach for separately accounting for soiling interannual variability similarly to the handling of weather. In this work we describe a transparent method for calculating soiling interannual variability and incorporating the results directly into Pvalue calculations. We first present a methodology section and then we provide results from applying the approach to 16 sites in the Southwest U.S. with well-established data on soiling rates.

II. Methodology

The Kimber soiling model [6] is commonly used to estimate soiling losses, where the basic assumption is that soiling occurs linearly during dry periods followed by cleaning or recovery through rainfall events above a minimum threshold. PVlib currently provides a free implementation of the Kimber model using Python [7]. The two primary inputs to the model are daily rainfall (available through PRISM for the continental U.S. [8]) and soiling rates for the site under investigation. Proposed utility scale sites are often subjected to an irradiance and soiling measurement campaign in order to capture data for reducing irradiance and soiling model uncertainty. For similar reasons NREL has been working to build a soiling data map through the extraction of soiling information from PV time series data [9, 10]. To examine the interannual variability of soiling losses we have selected 16 Southwest U.S. sites from the NREL soiling map that have soiling losses greater than 1% and therefore also report data on monthly soiling rates (see Fig.1). We simulate soiling losses for 20 years using the basic Kimber model with the following assumptions: cleaning to 99.5% occurs for daily PRISM rainfall totals greater than 2.5 mm, no grace period is included, the monthly median soiling rates are input from the NREL soiling map, and in the event that data isn't available for a specific month then the lowest median rate from all other months is used for that month. 20 years of simulation is chosen because 1999-2018 is currently available through both PRISM and NREL's free PSM3 satellite based solar irradiance data through the NSRDB [11]. As an NSRDB update is currently in progress it is expected that 1998-2021 can be run for the full paper.

It is expected that to best account for soiling variability that daily soiling losses be weighted by daily insolation totals or optimally as a loss within the appropriate step in the PV performance model. For example, a 5% raw soiling loss results in significantly lower energy loss during short sunny winter day as compared to long sunny summer day. If the PV system DC/AC ratio is significantly greater than 1 it is critical to apply the soiling losses within the PV model as system clipping can mitigate soiling losses and reduce interannual variability. Similarly, if the PV system contract mandates cleanings, these cleanings should be included in the soiling model to correctly capture the impact on interannual soiling variability. In this work we use the algorithms within PVlib's ModelChain class to model hourly PV energy output for each of the 16 sites in Fig. 1. The baseline model is 100 megawatt single-axis tracking system (±60°) with a 0.33 ground coverage ratio, and DC/AC ratio of 1 (no clipping). Each of the 20 years the monthly soiling losses resulting from the Kimber model are input into the PV model with the given years PSM3 irradiance to generate an annual energy production for that year. Specifically, the effective irradiance profile within the PVlib model is multiplied by the monthly soiling loss factor. The simulation is performed with and without soiling to estimate the impact soiling has on interannual performance variability.

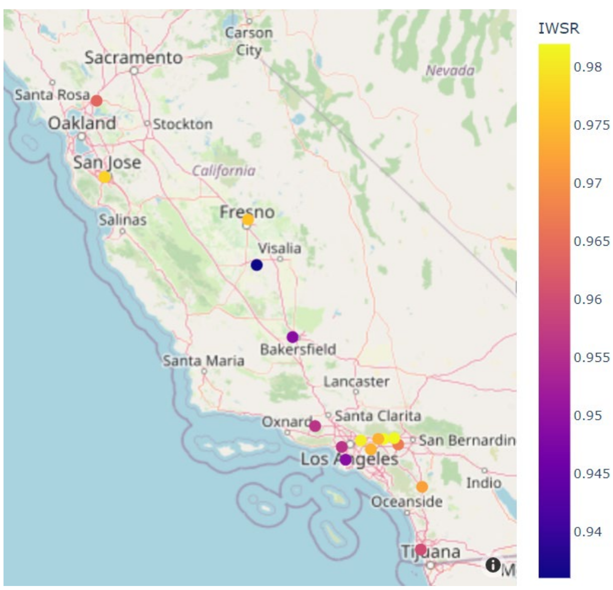

Fig. 1. 16 sites selected from the NREL soiling map.

Pvalues are generated with and without soiling using a Monte Carlo analysis. 20,000 samplings are made from the 20 years of modeled performance data in conjunction with a sampling from a normal distribution for the PV models uncertainty, which is defined by a mean of zero with a ± 2.5% uncertainty at one standard deviation. This uncertainty distribution is intended to represent all the uncertainties that go into the P50 PV model (for example, uncertainties associated with the soiling and irradiance models are considered here). This uncertainty is typically calculated by IEs through various evaluations of the plant specific model, including factors such ground tuning of satellite irradiance and site soiling measurement campaigns. Here we are not evaluating individual PV plants and therefore we apply a general model uncertainty to all sites. In the full paper we intend to examine a separate accounting for soiling uncertainty based on the range of soiling rates provided for each month on the NREL soiling map.

III. Soiling Variability Results

The box and whisker plot in Fig. 2 provides the 20 years of energy-weighted soiling losses for each of the 16 sites. The average soiling losses range from 4.3-15.5% while the full range of soiling losses varies significantly depending on the site. For example, sites 5219 and 5286 are examples of low to moderate soiling with only about a 5% spread in losses over the 20 years. Alternatively, site 7052 has a median loss of about 15% and the spread of values over the 20 years is about 20%. It is also clear that for 20 years the data is not necessarily normally distributed.

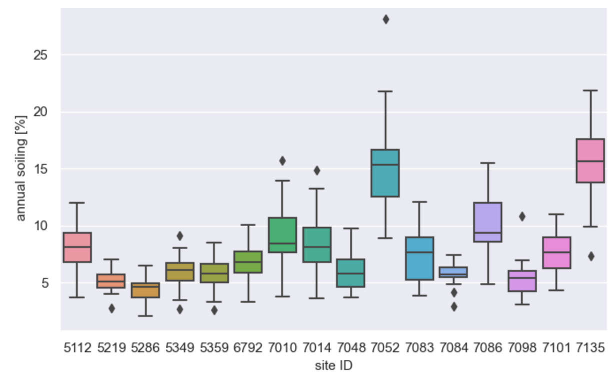

Fig. 2. Box and whisker plot of annual energy-weighted soiling losses for each site (the box represents the interquartile range, whiskers represent the maximum and minimum boundaries if an outlier/diamond is not plotted).

Fig. 3 provides a box and whisker plot comparing the interannual variability of energy production for models with and without soiling (given as percentage change from the P50 for each model). It is important to note that for some sites interannual variability over 20 years is significantly different between the models with and without soiling. This demonstrates that the relationship between irradiance, rain, and soiling each year can be important to accurately representing interannual variability.

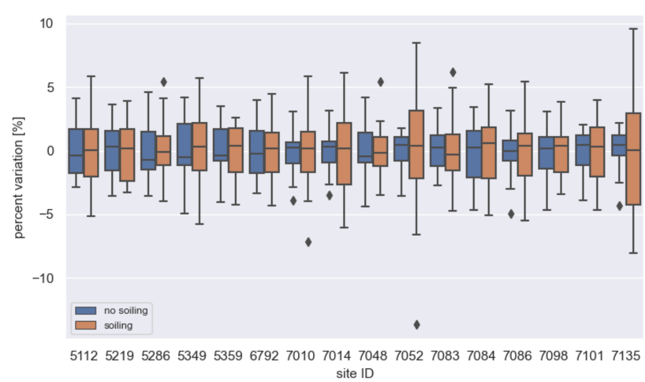

Fig. 3. Interannual variation of PV energy generation with and without soiling (the box represents the interquartile range, whiskers represent the maximum and minimum boundaries if an outlier/diamond is not plotted).

IV. PVALUE RESULTS

Table 1 provides the spread of Pvalues (P1-P99) generated from the Monte Carlo simulation considering PV interannual performance variability and ± 2.5% model uncertainty at one standard deviation. Mean and standard deviation of soiling for each site are provided for context. The final column in Table 1 provides the increase in the spread of Pvalues when soiling is included in the interannual performance calculations. For three of the sites the Pvalue spread is nearly the same (± 0.1%). The other thirteen sites show the Pvalue spread increase anywhere from 0.4-12.7% showing that including soiling within interannual variability can be especially important for PV plants with higher soiling rates. While these results will vary with system design, especially DC/AC overbuild or the inclusion of contracted cleaning schedules, they do point to the importance of accounting for interannual soiling variability within Pvalue calculations.

TABLE 1. Pvalues:16 sites with and without soiling

Site	Mean soiling [%]	Soiling stdev [%]	P1-P99 no soil [%]	P1-P99 soiling change [%]
5112	8.0	1.9	14.9	3.0
5219	5.1	1.0	14.7	0.4
5286	4.3	1.1	15.4	0.8
5349	5.9	1.5	15.5	1.8
5359	5.7	1.4	14.8	-0.1
6792	6.8	1.7	14.9	0.8
7010	9.0	2.6	14.1	4.6
7014	8.7	2.8	13.7	4.9
7048	6.1	1.7	14.9	0.1
7052	15.6	4.1	13.4	12.7
7083	7.5	2.4	13.9	2.9
7084	5.8	1.1	15.2	1.2
7086	10.0	2.6	14.5	2.9
7098	5.4	1.7	15.1	-0.1
7101	7.6	1.9	13.7	1.9
7135	15.5	3.7	13.6	9.8

V. CONCLUSIONS

This work has demonstrated a methodology that can be applied through existing tools (the PVlib Kimber model, the NREL soiling map, PRISM, and NSRDB) to estimate interannual soiling variability. The methodology was applied to 16 sites in the Southwest U.S. as a demonstration of what interannual soiling variability can look like. In the case of these 16 sites, the mean soiling ranged from 4.3% to 15.5%. The inclusion of soiling calculations within 20 years of annual PV performance calculations resulted in the Pvalue spread (P1-P99) increasing from -0.1% to 12.7%. These results are exemplary as actual results with depend on specific PV system design parameters like DC/AC overbuild and contract features around operations and maintenance (specifically cleaning schedules). Additionally, the specific calculated PV model uncertainty propagated into the Monte Carlo simulation will impact final results.

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