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A Method to Extract Soiling Loss Data From Soiling Stations with Imperfect Cleaning Schedules

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***Abstract* — Typical PV soiling stations determine the natural soiling losses by comparing the output of a naturally soiled PV cell to that of a PV cell maintained in the clean state. Inadequate cleaning frequency, equipment failure, or human error provides opportunity for the cleaned cell to soil, directly resulting in error in the reported soiling ratio. This work investigates an algorithm to automatically detect and correct the data stream for errors associated with soiling of the clean cell. The methodology is tested on several soiling stations with irregular cleaning schedules as well as two soiling stations where both ideal and imperfect cleaning schedules are in place. The initial results show that the algorithm can reduce error associated with imperfect cleaning but also confirms the benefits of maintaining an optimal cleaning schedule.**

I. Introduction

PV soiling losses (energy generation losses due to dust on a PV surface) can be in the range of 0-6% in the United States and can be 20-80% in dusty regions of the world like the Middle East [1]. Lost energy generation directly equates to lost dollars and therefore as the PV market has expanded into the dusty regions of the world, soiling research has increased dramatically. Soiling research spans a range of topics including: soiling loss measurements and associated equipment, dust characterization, soiling adhesion mechanisms, soiling loss modeling, automated cleaning systems, and module surface coatings to reject soil adhesion. This work seeks to add to the PV community's ability to measure and report soiling loss data so the data are both reliable and well understood. Soiling stations are being used around the world to report soiling losses which are then used by various parties such as financiers, performance modelers, and planners of system operations and maintenance (O&M). While soiling stations can vary in design (i.e. cell versus module measurements, short-circuit current versus peak power tracking, tilt angle, and choices on supplementary meteorological equipment), in most stations the soiling loss measurement is the ratio of the output of a naturally soiled PV device to the output of a clean PV device. This type of device is well described in the literature; including measurement uncertainty associated with errors in mounting, calibration drift, angle of incidence effects, and temperature effects [2-5]. The fundamental measured ratio between a dirty and clean PV device, however, is not always systematically treated. While the dirty device is allowed to soil based on natural events, the cleaned cell is maintained in the "clean" state by manual or automated cleaning practices. The authors of this work have experienced a range of soiling stations where the "clean" state is assumed because daily, weekly, biweekly, or other irregular cleaning intervals are applied to the clean cell. Although "clean" in the purest sense would imply no soil particles on the PV device, this is not realistic for any outdoor device. Rather, the amount of soiling allowed on the clean cell impacts the uncertainty of the reported soiling ratio. The level of tolerable uncertainty will generally depend on the end needs of the data user and therefore are not defined in this work. On the other hand, if nothing can be established in regards to the uncertainty of an imperfect soiling ratio (it could be in the range of 0-100% losses), the data are of no use. Therefore it is valuable to be able to somehow quantify the uncertainty of an imperfect soiling ratio and develop methods to glean valuable information from this data. Hereafter, a methodology is presented to quantify errors in an imperfect soiling ratio, correct for these errors, and quantify the uncertainty based on these errors.

II. Methods for soiling loss extraction

A. Soiling Stations and soiling metrics

This study is based on the data recorded by ten soiling stations installed in the southwestern United States. Each soiling station has two identical PV cells, where one is intended to be the clean device and the other is allowed to naturally soil. The ten sites were chosen because the cleaning was done manually and the intervals of cleaning were not consistently achieved. Using the same method employed in [3], a daily soiling ratio (SRatio) is calculated, obtained as the ratio between the daily mean short circuit currents of the two cells. A soiling ratio of one represents clean conditions, and its value decreases with the soiling. Short circuit currents, irradiances and weather data are recorded each minute and converted into hourly data. Only data occurring between 11AM and 1PM have been considered to minimize variation due to angle of incidence effects. Performance plots of each soiling station have been visually checked in order to remove any data due to equipment malfunction, shading, or performance outside of reasonable bounds.

B. Algorithm for correcting imperfect soiling ratio data

An algorithm has been developed to correct for errors in the measured soiling ratio due to infrequent cleaning and therefore soiling of the clean cell. Fig. 2 provides a flow chart of the algorithm where key points are as follows: 1) Noise is defined as two times the mean of all upward shifts in the SRatio not associated with precipitation, 2) Downward shifts in the SRatio that are twice or more than the noise are interpreted as a cleaning of the clean cell and the SRatio following the shift is an accepted data point. 3) In cases where precipitation coincides with an upward shift in the SRatio (twice or more than the noise) both cells are considered clean and the SRatio is set to one, 4) SRatios between acceptable data points are determined by connecting lines between the acceptable data points (note the majority of measured data points are rejected). Fig. 1 is a cartoon of soiling station data that helps to elucidate these key points. The black SRatio points demonstrate measurements of the SRatio over 50 days. The SRatio starts at one because both cells have been cleaned and then it has a noisy trend until day 14 where a downward shift is detected. The red triangle is considered a true measurement of the SRatio and a line is drawn between day 1 and day 14. On day 30 an upward shift and rain are detected so the SRatio is set to one. The SRatio measurement on day 29 was not acceptable because of unknown soil level on the clean cell (i.e. no downward shifts were detected beyond day 14). The SRatio slope between day 1 and day 14 is projected to day 29 because it is the most recent estimate of what is occurring at the site. No shifts are detected between the rains on day 30 and day 50 and so no new information is obtained about the rate of change in the SRatio. An estimate is then assumed by using the slope that was used in the previous soiling period. This assumes that both cells soil together between days 30 and 50 and that the 14 day cleaning schedule was missed. It is possible that soiling could have been minimal in this time period but the authors considered it more conservative to assume soiling is occurring.

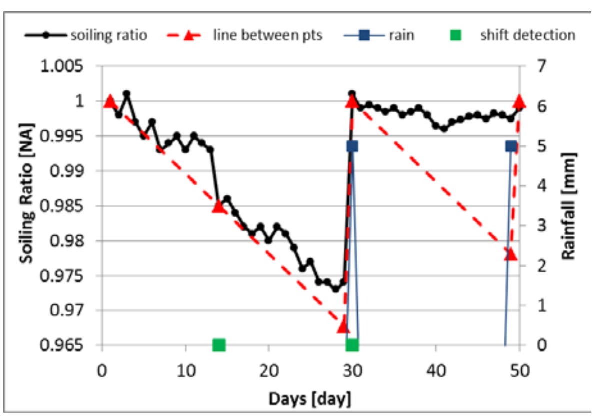

Fig. 1. A cartoon of key points in the algorithm for correcting an imperfect soiling ratio.

Calculate all daily changes in the SRatio
$\Delta SRatio_i = SRatio_i - SRatio_{i-1}$

Calculate Noise using all $\Delta SRatio_i > 0$
Noise = $\overline{\Delta SRatio_i}$

Detect significant shifts in $\Delta SRatio_i$
<u>$\Delta SRatio_i \geq 2\cdot$Noise</u>
→ If also precipitation $\Delta SRatio_i$ reset to 1
→ No precip then $\Delta SRatio_i$ = constant until next significant shift
<u>$\Delta SRatio_i \leq -2\cdot$Noise</u>
→ $\Delta SRatio_i$ is accepted (clean cell cleaning)

Establish corrected profile for $\Delta SRatio_i$
- For each significant shift of $\Delta SRatio_i$ an algorithm datapoint is stored; $aSRatio_j$
- Starting at $aSRatio_{j=0}$ = 1 extract a slope between the j and j+1 points for $aSRatio_j$

→ If slope < 0 accept and project between the times associated with j and j+1
→ If slope > 0 and no precipitation occurs on j+1 then the slope is reset to 0 and projected forward from the $aSRatio_j$
→ If slope > 0 and precipitation occurs on j+1 then the slope from $aSRatio_{j-1}$ to $aSRatio_j$ is projected to the date immediately before the date associated with j+1.
→ The accepted slope for each period is started at the end of the previous slope so the corrected profile has continuity. For this reason $aSRatio_j$ is not necessarily on the corrected profile.

Fig. 2. A flow chart that explains the steps taken in the corrective algorithm.

Fig. 3 presents an example of how the SRatio correction algorithm is applied to an actual soiling station in the southwest United States. The black data points are the measured SRatio data and red lines connect each set of data points that the algorithm accepts. Days with precipitation are marked in blue and the downward shift detection is marked in green. The period from July through October shows a series of downward steps that are believed to be cell cleanings about every two weeks. The fact that the steps are easily visible indicates that significant soiling is possible at this site on the clean cell over two weeks. This site is an ideal case for the correction algorithm because the dry period is multiple months and data points every two weeks make it possible to still see the longer downward trend.

TABLE I

AVERAGE SOILING RATIOS DETERMINED FOR 10 SITES IN THE SOUTHWESTERN UNITED STATES. THE RATIOS ARE GIVEN FOR THE MEASURED VALUES (SR_M) AND BASED ON THE CORRECTIVE ALGORITHM (SR_C). ALL VALUES ARE GIVEN AS PERCENTAGES

SITE	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
SR_M	99.9	99.6	99.8	95.9	99.2	99.1	93.6	99.4	99.9	99.9
SR_C	99.5	99.1	98.8	95.4	98.8	97.5	91.9	99.5	99.4	99.4
U	0.2	0.6	0.9	1.9	1.7	2.1	3.3	0.4	0.6	0.6

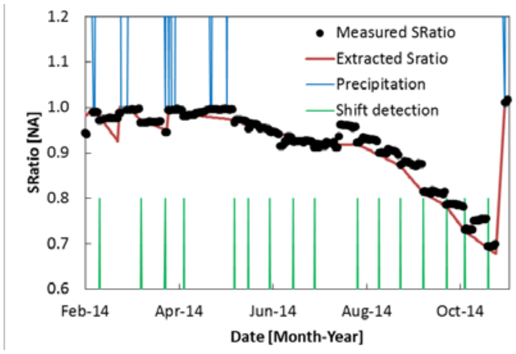

Fig. 3. Applying the correction algorithm to the measured SRatio for one site in the southwest United States.

B. Uncertainty determination

A major assumption of the SRatio correction algorithm is that the soiling rate (slope of the SRatio) is linear between accepted data points. It is possible that over an interval like two weeks that soiling rate could vary for many reasons (i.e. pollution from a worksite, and agricultural activity or changes in site conditions). Without actually measuring such deviations one cannot quantify the specific effects but errors in the SRatio are likely to occur that are both positive and negative (therefore canceling each other in an average result). A data set is being collected to analyze such variation but the magnitude of shifts in the SRatio at each cleaning also provide information about the worst case uncertainty for the average SRatio. For example, if after two weeks the clean cell is cleaned and the SRatio shifts by 10%, the worst case scenario is that a large soiling event occurred immediately after the previous cleaning and the SRatio was in 10% error for the entire 2 weeks. It is unrealistic to assume this would always happen and therefore the magnitudes of all the detected downward shifts are averaged and this value is reported as the site uncertainty. A long term data set with side-by-side PV cells cleaned at different frequencies would provide a more thorough uncertainty analysis but the above value is useful because it is conservative (the most extreme soiling loss case is estimated) and it will increase both for dirtier sites and for longer periods between cleanings. The reported uncertainty therefore provides a measure of the impact of less frequent cleanings.

III. RESULTS AND DISCUSSION

A. Results for average soiling ratios

Table I provides the average SRatios for the 10 sites in this study. ***SR_M*** is the average of all the daily measured SRatios while ***SR_C*** is average of the daily values per the corrective algorithm. The site uncertainty, ***U***, as described in the previous section, is also given in Table I.

B. Discussion

The results in Table I show that the 10 sites have measured soiling ratios from 93.6% to 99.9% and the corrected values range from 91.9% to 99.5%. Some sites that have measured losses less than 1% have corrections on the order of tenths of a percent, while others have corrections on the order of a few percent. Site 6 has the greatest correction, reducing from 99.1% to 97.5%. While the model has yet to go through a true validation, the fit in Fig. 3 suggests that it is possible to automatically detect soiling station cleaning events and then use these events to construct a correction for a long term soiling trend. It is interesting to note that the uncertainty values as defined in the previous section match very closely to the magnitude of the correction for each site. Although the algorithm and uncertainty are related to each other, the algorithm applies a series of complex steps and assumptions whereas the uncertainty represents only the average of all the errors in the SRatio for just the days where the SRatio shifts downward (believed to be cleanings of the clean cell).

C. Validation efforts

In order to draw further conclusions on the value and uncertainty of the proposed SRatio corrective algorithm, two soiling stations were built and recently deployed to gather validation data. Fig. 4 shows a picture of one of the validation stations which each have four PV cells. One of the cells is left to naturally soil while the others are intended to be cleaned daily, weekly and every other week. One of the stations was deployed at the University of California, Riverside where past years have shown an average annual soiling losses of ~ 4-6% [6]. The second station was employed in Golden, Colorado where the average annual soiling loss is typically less than 1%.

Due to this low soiling loss in Golden, artificial soiling was employed to increase the soiling rate. A leaf blower was used on an approximate daily basis to agitate soil and other matter on the ground adjacent to the soiling station, effectively creating a short term dust cloud around the soiling station. The Golden station was intended for a short term proof of concept while the Riverside station was intended to be an actual field validation.

Fig. 4. Deployed PV cells cleaned daily, weekly, every 2 weeks, and not at all to validate the results of the correction algorithm.

Golden Station

The intent of the Golden station was to provide a first pass validation of the correction algorithm while waiting for longer term data from a field site with substantial soiling. Although some lessons were learned from the Golden station the data did not provide a simple first pass validation. The artificial soiling station presented the following challenges and lessons:

1) Leaf blower soiling resulted in losses on the order of several percent per day (greater than any typical U.S. location).

2) Leaf blower soiling rates were not as linear as what is often seen in the field and the SRatio seemed to bottom out near 0.5.

3) Precipitation frequency was on the order of every 2 weeks and therefore prevented obtaining a useful comparison between weekly and biweekly cleaning.

4) The majority of precipitation was in the form of snow. The typical experience with PV systems at NREL is that, on the first sunny day following a snow, the solar panels will be warmed and the snow will slide off all of the panels in a matter of minutes, resulting in a complete cleaning. Although the soiling station reference cells were mounted at latitude tilt, the cells did not behave the same in response to snow as full size panels. On some days following snowstorms, the snow was seen to slowly melt and partially slide on the small reference cell. The data showed that, in several cases, this resulted in partial cleaning over several days (the SRatio increases over multiple days following precipitation, see the yellow circle on Fig. 5). The corrective algorithm was not designed to correct for partial cleanings or for cleanings that occur over multiple days due to melting snow and therefore it performed poorly in these time periods.

Fig. 5 provides the time series SRatio data for the daily and weekly cleanings as well as the result of applying the algorithm to the weekly cleaning data. The actual average measured SRatio per the daily cleaning was 0.82, the uncorrected average from weekly cleaning was 0.86, and the result from applying the corrective algorithm was 0.78. The soiling loss was over estimated during the snow melt off periods and therefore the corrective algorithm over predicted the soiling losses and therefore the corrective algorithm provides no clear benefit.

Riverside Station

At the time of preparation of this paper data was only available from the Riverside station from 3/6/2017 through 5/9/2017. Students provided the cleaning support and therefore cleaning did not occur on the weekends or during spring break (3/25/2017-4/3/2017). Further issues resulted in no cleaning occurring from 4/8/2017 – 4/25/2017. Although this results in only approximately 7 weeks of data where the true soiling ratio was measured (daily cleaning), the corrective algorithm was still run on various data streams and the results for the biweekly cleaning are shown in Fig. 6.

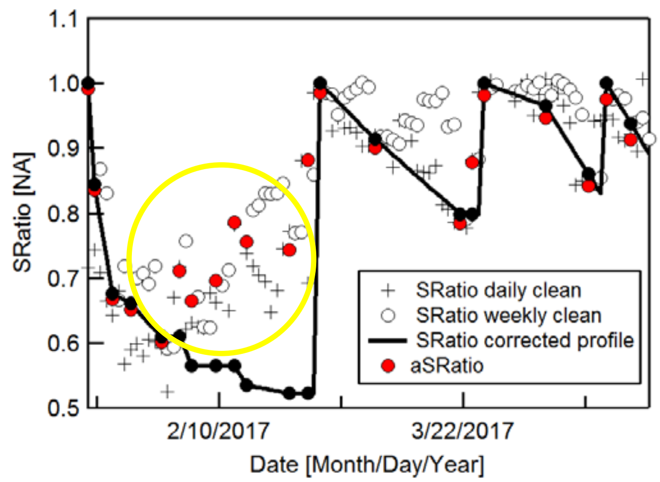

Fig. 5. Golden, Colorado soiling station with artificial soiling. The soiling ratio based on daily and weekly cleaning is shown along with the soiling ratio correction algorithm as applied to the weekly cleaning data. The corrective algorithm is shown as a series of black lines that connect all the black dots. The black dots align with the dates for which there are also red dots. The red dots are values where shifts are detected which are used to construct the corrected SRatio. In February (yellow circle) there were several snow events (snow dates not shown on the graph) that caused partially cleaning and therefore the true SRatio (daily cleaning) improves. Although upward shifts were recorded by the algorithm (red dots) the snow did not occur on the days of the upward shifts and therefore the algorithm fits with a zero slope. The cleaning by snow usually occurs in the days following the snow storm. No changes were made to account for the effects of snow because typical high soiling sites are desert environments where snow is not expected to be a factor.

Although the data collection period is quite short, the graph clearly demonstrates that cleaning every two weeks in Riverside does not result in an accurate SRatio. The first three periods between cleanings result in a SRatio that trends upward. This suggests the clean cell actually soils at a slightly faster rate than the cell that is only cleaned by rain or natural events. The average SRatios (for the entire data collection period) for the different cleaning frequencies are as follows: estimate of the "true" SRatio = 0.98 (daily data with corrections applied for the noted time period where no cleanings were performed), SRatio measured using weekly cleaning = 0.99, SRatio after applying a correction to the weekly cleaning data = 0.98, SRatio measured using biweekly cleaning = 0.99, SRatio after applying a correction to the biweekly cleaning data = 0.98. The corrective algorithm is successful in predicting the estimate of the "true" SRatio based on both weekly and biweekly cleaning cells but caution must be taken in using these results for the following reasons: 1) The "true" value is only an estimate due to the weeks where cleaning support was not available, 2) The data only span 9 weeks and therefore should be considered preliminary, and 3) No extended soiling period has been experienced and therefore the soiling losses are generally low regardless of the cleaning frequency.

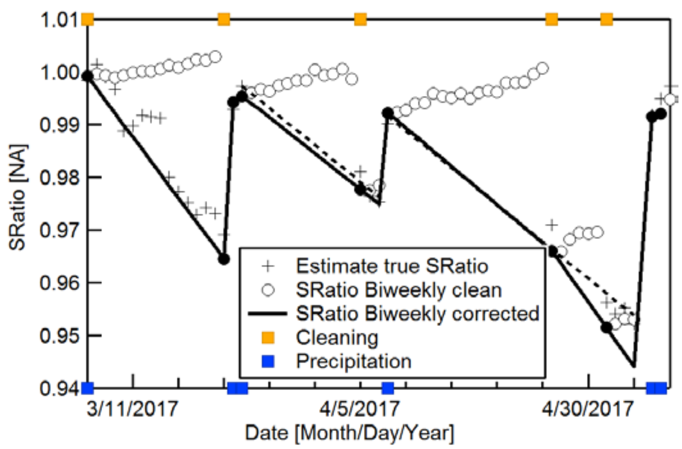

Fig. 6. The soiling ratio measurements based on the biweekly cleaned cell are shown in comparison to the estimate of the true soiling ratio and the correction as applied to the data from biweekly cleaning. A dashed line is shown where the true soiling ratio was estimated as daily cleaning did not occur in this time period. The data from biweekly cleaning illustrates the problem with infrequent cleanings. The trend of the soiling ratio appears to be positive between cleanings. There has been anecdotal evidence that a regularly manually cleaned cell can soil at a slightly different rate than a cell that is only cleaned by rain but the trend in this graph could also be a product of noise.

IV. Preliminary Conclusions

Soiling stations are being deployed all over the world to determine information about the soiling losses on PV systems. These soiling stations provide a SRatio between a dirty and cleaned PV device but often the SRatio has significant error because the cleaned cell is also allowed to soil, depending on the cleaning interval. If no information is known about the level of soiling on the clean cell, then the true SRatio is also unknown. An algorithm has been presented that automatically detects cleaning events for the clean cell and therefore establishes trustworthy data points in the time series data set for the SRatio. These data points have been used to both determine a worst case uncertainty for the annual average measured SRatio and to estimate a time series correction for the SRatio. As should be expected, the uncertainty for a site increases when the soiling rate is greater and the time between cleanings is greater. The uncertainty metric ultimately provides a way to interpret and use data that otherwise is difficult to trust.

An initial effort was presented to validate the proposed SRatio corrective algorithm based on an outdoor artificial soiling station in Golden, Colorado and a representative field soiling station in Riverside, California. The Golden soiling station presented several limitations but it demonstrated that the corrective algorithm failed to appropriately handle partially cleanings that occur when snow melts on the surface of PV reference cells. This is not surprising as the algorithm was designed around complete cleanings; either manually performed or due to significant rainfall. Validation based on the station in Riverside, California is very limited due to the short data collection period. The initial results from the Riverside station suggest that the corrective algorithm has potential for sites when cleaning events result in full, rather than partial, cleaning. Both weekly and biweekly cleaning of the clean cell underestimated the losses and the algorithm was able to correct for this. Further validation efforts are necessary to determine if the corrective algorithm should be more broadly used.

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