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Reducing Interanalyst Variability in Photovoltaic Degradation Rate Assessments

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***Abstract*—The economic return on investment of a commercial photovoltaic system depends greatly on its performance over the long term and, hence, its degradation rate. Many methods have been proposed for assessing system degradation rates from outdoor performance data. However, comparing reported values from one analyst and research group to another requires a common baseline of performance; consistency between methods and analysts can be a challenge. An interlaboratory study was conducted involving different volunteer analysts reporting on the same photovoltaic performance data using different methodologies. Initial variability of the reported degradation rates was so high that analysts could not come to a consensus whether a system degraded or not. More consistent values are received when written guidance is provided to each analyst. Further improvements in analyst variance was accomplished by using the free open-source software RdTools, allowing a reduction in variance between analysts by more than two orders of magnitude over the first round, where multiple analysis methods are allowed. This article highlights many pitfalls in conducting "routine" degradation analysis, and it addresses some of the factors that must be considered when comparing degradation results reported by different analysts or methods.**

***Index Terms*—Degradation rate, photovoltaics, RdTools, round-robin.**

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I. Introduction

PHOTOVOLTAIC (PV) costs have declined over the past 40 years due to a combination of market mechanisms (economy of scale, research, and development investment, public subsidy) and technical improvement (increased cell efficiency, module supply chain, and materials cost reductions) [1]. Continuous technological advances in cell efficiencies and module materials can be expected; therefore, products installed currently may differ from legacy systems and may not have a long history of field performance. The need exists, therefore, to assess the long-term performance health of different PV technologies quickly, accurately, and consistently. Degradation rates (R_d) quantify the slow and gradual loss of performance and are typically expressed relative to previous performance in %/year. These rates are also known by less ambiguous terms such as performance loss rates or rates of change [2], [3], and we take the convention here of a negative value indicating performance loss.

Degradation rates (or, in more general terms, degradation curves) have been aggregated from published reports and summarized by some of the authors before [4] and in other studies. Many technical factors have been found influencing PV system degradation rates, including the cell technology, climate, and mounting method [5]–[9]. However, the method and details of the analysis itself can also introduce significant variation in the result [10]. To be able to compare results across multiple analysts and methods and to isolate intrinsic variations between PV technologies, this interanalyst variability must be studied and controlled. Further motivation includes an upcoming analysis and comparison of performance loss rates under the auspices of the International Energy Agency—Photovoltaic Power Systems Programme Task 13 [11].

The need for a R_d performance benchmark is clear given the many methods for calculating performance loss. This remains a very active field of research, especially with the advent of machine-learning algorithms [12], [13]. Because a detailed review of degradation methods has been covered previously, this

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article highlights only some techniques that were known to have been used for this effort [14]. The most direct method may be to remove data that are not representative of the PV performance, such as when the system or the irradiance sensor is shaded, soiled, or covered in snow, followed by a standard least-squares regression (SLS) to extract the long-term trend. Although this is the most direct method, the regression approach has disadvantages such as high leverage and sensitivity to outliers [15]. The month-to-month approach uses a physical model to evaluate the data in monthly increments and combines them with a weighted regression to counter the disadvantages of SLS [16]. The year-on-year methodology, which compares the performance of the system at any given point in time (e.g., day, month) with that same point the previous year, is another way to eliminate regression disadvantages [17]. Some of the authors subsequently showed that the impact of seasonal soiling and irradiance sensor drift could be minimized when this approach was combined with clear-sky modeling [18]. This combined methodology led to the introduction of RdTools, a publicly available open-source software to determine R_d [19].

The concept of an analyst intercomparison for PV performance is not new, but previous efforts have focused on predictive modeling of initial PV performance. One example was a blind study in which different users were provided with system configuration details and a year of meteorological data and asked to predict the energy production of several PV systems [20]. No equivalent study exists to date for long-term PV performance and degradation rate extraction.

The motivation of this article is to, first, quantify the impact that different analysts using different methods can have on degradation assessment and, second, demonstrate the progress that has been made in developing a consistent evaluation of fielded PV systems using the methodology developed in [18]. This article is organized as follows. Section II shows and discusses the results of an interlaboratory study when a diverse range of PV analysts examine the same datasets, and Section III describes specific findings of the comparison, including identifying the areas in which the different analysts may have differed, thus, introducing scatter into the results.

II. Interanalyst Study

The intent of this study is to evaluate the deviations encountered by different analysts on real-world systems containing some challenges frequently encountered in fielded systems. Analysts were supplied with unprocessed data from three separate systems ranging in duration from 4 to 10 years. This length of time was previously found to be sufficient for determining accurate R_d values [15]. The first two systems to be analyzed are a 1-kW research system located at the National Renewable Energy Laboratory (NREL) and a 6.3-kW system from Desert Knowledge Center in Alice Springs, NT, Australia. Raw data are available at [21] and [22], respectively. Both systems are open-rack deployments of Sanyo 200–210 W HIT modules. The final three systems are commercial-scale, ground-mount installations located in central California, USA. These scaled production data were provided anonymously by a commercial partner, without identifying metadata. Therefore, certain

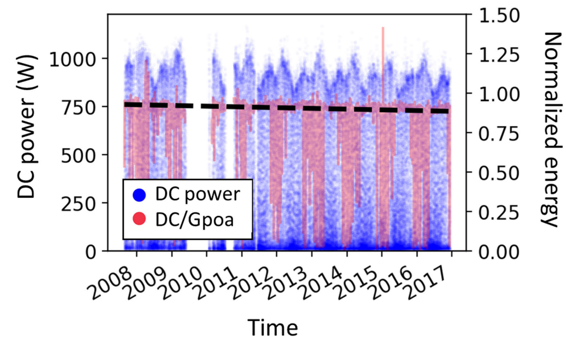

Fig. 1. DC power (left axis) of a small and relatively clean test system at NREL that was used in the interlaboratory study. The right axis shows array responsivity including the degradation rate trend.

operational details of the systems—including specific size, location, and module technology—are unavailable, but anonymized data may be made available.

The electrical and weather data were collected in either 1 or 15-min increments, shown as an example in Fig. 1 for the 1-kW NREL system. Irradiance was measured by photodiode and pyranometer both horizontally and in the plane of array (POA), and wind speed, ambient temperature, and module temperatures were supplied where available. Although the systems were relatively well tended, measurement irregularities remained in the raw data, which is often the case with typical field data. Examples include data outages in the NREL data, visible in Fig. 1, accompanied by a change in data frequency from 15 to 1-min interval. Some locations were characterized by a high-soiling environment whereas others, such as at NREL, had negligible soiling. Additionally, the commercial systems in California contained substantial inverter clipping, which could either be considered or ignored, depending on analyst preference.

In the first round of the analyst intercomparison, six volunteer analysts used their preferred method to assess the degradation of the five systems. No specific guidance was provided regarding which degradation methodology to use, how outliers or erroneous data should be handled, or whether system degradation (including inverter clipping) or module degradation (excluding clipped data) should be reported. Not surprisingly, no consensus was reached among the analysts, with a high variability in the annual degradation rate reported for each system. There was not even consensus over whether the systems were improving or degrading with time, with some analysts reporting large increases in power, and others reporting substantial degradation over time.

The results for this first round of analyst comparison are shown in Fig. 2, where different analysts are indicated by color, and different systems are indicated by symbol. Because systems are changing at different rates, the actual reported performance loss rate (e.g., –1%/year degradation or +0.5%/year improvement) is normalized by the median value reported by all analysts. In other words, the median reported rate of change for each system coincides with 0%, and each analyst's response is plotted by its deviation from the median or the consensus value for each system. In this first round of comparison, a substantial spread exists in reported values, with an overall variance among analysts being $\sigma^2 = 0.745$ [%/year absolute].

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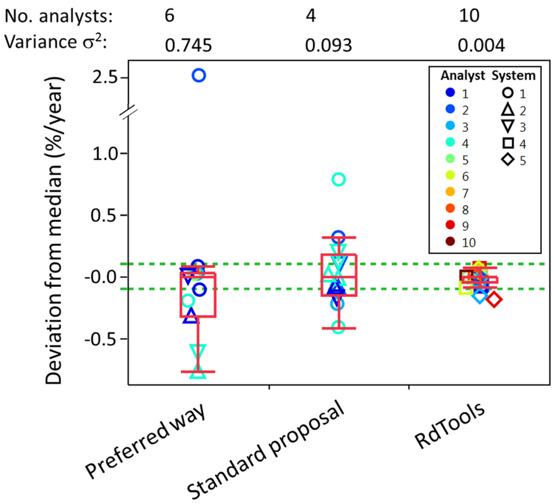

Fig. 2. Deviations from the median result of all analyst of the round-robin study. Different analysts are color-coded, and PV systems are symbol-coded. The number of analysts and the variance of all results are given above the graph. As a guide to the eye, tight intervals of ±0.1%/year are shown.

The causes for the wide spread in results are addressed in more detail in Section III, but they fall generally into broad categories: instrumentation errors (sensor drift, temperature anomalies), methodological differences (regression techniques more sensitive to outliers), and reporting conventions (report module-only degradation or system degradation inclusive of soiling and inverter clipping). The most common methodology used by the analysts was a simple SLS regression approach that can easily lead to different results, as further discussed in Section III.

Mindful of the preventable causes of analyst variability, an effort was undertaken to develop a written standard, intending to define key terms and provide suggestions to the analyst [23]. The intent of this document is to provide guidance to some aspects of the general decision process outlined in Section III. However, the method relies heavily on the application of a moving stability and an outlier filter in combination with an uncertainty minimization process [10], [24]. In addition, because the documented procedure also employs linear regression of monthly temperature-corrected Performance Ratio (PR) values, it fails to sufficiently address issues of sensor drift and soiling. Lastly, it was the analyst's responsibility to implement the instructions into the preferred software, exposing it not only to human error but also to differences in software algorithm, e.g., differences in optimization methods.

Results from the second round of analyst intercomparison, where the draft standard was used to enforce more consistent methodology, are shown in the second column of Fig. 2. Four analysts from different organizations contributed their results for three of the systems described above. It is clear that some of the outliers were eliminated, reducing the overall variance significantly to $\sigma^2 = 0.093$ [%/year absolute]. However, the remaining results were still not as tight as desired, with an interquartile range largely unchanged from the first round, leaving an unacceptable uncertainty in the performance assessment.

Written documentation is a necessary first step for consistent results; however, this strategy may be far more conducive to indoor experiments in a controlled environment than to the analysis of outdoor data that are "imperfect" in myriad ways. Mistake-proofing (or poka-yoke) is a concept that seeks to reduce inadvertent human-induced errors in the 6-Sigma methodology [25], [26]. Mistake-proofing in this context consisted of using the software algorithm, RdTools, to provide guidance through the decision process and that uses an inherently more robust methodology. The algorithm has been presented in more detail previously [27], but is briefly summarized here.

1) Performance data are normalized by temperature and irradiance. Either a local irradiance sensor or modeled clear-sky irradiance (less susceptible to drift over time) is used. Temperature is either ambient (Tamb) or module (Tmod) temperature.
2) In a filtering step, nighttime, unphysical, and clipped data due to high dc–ac ratio are removed. If clear-sky irradiance is used, an additional filter removes nonnuclear periods.
3) Hourly or minutely data are aggregated to daily irradiance-weighted values.
4) A year-on-year degradation regression is conducted in which a series of annual loss rates are calculated between daily aggregated points separated by 365 days. The median of this distribution is identified as the system's R_d. This method has been shown to be less susceptible to data anomalies and seasonal soiling. It is also less susceptible to outliers caused by nonseasonal soiling or other irregular events compared to traditional regression-based methods [15], [17].

Results from a third round of intercomparison involving ten analysts and two systems are shown in the final column of Fig. 2. The analysts' expertise with the RdTools software varied greatly. Some were familiar with the algorithm or had helped with its development. Other analysts were unfamiliar with RdTools prior to this article or had not analyzed PV field data before but were at least familiar with Python programming language in which RdTools is written. Finally, some analysts had no background in either field performance data, RdTools, or Python prior to this article. Despite these differences, the analysts all achieved similar results that fell almost exclusively within the very tight interval of 0.1%/year using RdTools. Two slight deviations did result when analysts used only a subset of the data instead of the complete dataset. Overall, the variance, the squared deviation of all analysts, was reduced by more than two orders of magnitude, which is an encouraging result for consistent reproducible PV performance evaluations. This fact has real-world consequences—the large Round-1 R_d analyst variability when applied to a 25-year system lifetime represents a 10% uncertainty in expected energy yield. By Round 3, the uncertainty related to analyst variance is reduced to a negligible factor. The entire evaluation period of this article took several years to complete; thus, the number of analysts varied from round to round for practical reasons despite an effort to keep it consistent. However, we had several analysts that were available for all evaluation rounds.

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In summary, we are not trying to claim that the methodology used is the best or most accurate at identifying system degradation rates. We merely state that without a method of controlling or guiding the many decisions of a PV performance analyst, a large range of possible outcomes could result. This is investigated in more detail in the following section.

III. Decision Trees

A thorough analysis of the initial intercomparison results identified some of the difficulties encountered by analysts in assessing long-term PV performance data. This can best be captured in a series of decision-tree figures that will help explain some of the results exhibited in the last figure.

Superficially, assessing long-term PV performance appears to be a simple task of collecting data and determining the long-term trend, often by means of a linear regression. However, "good-quality" outdoor data may look like the graph of Fig. 1. A small signal-to-noise ratio is caused by the diurnal and seasonal cycles, as well as outliers and two outages. This dataset exemplifies a relatively "clean" dataset because no unphysical and erroneous data or stuck sensors can be seen. Nevertheless, the nontrivial task is to distill a trend from this cloud of data and describe it by a degradation curve with a single linear slope or other nonlinear trend, and associated confidence interval [28]. To determine this trend, the analyst is faced with a series of important decisions, some of which may be subjective and may depend on the ultimate interest of the analyst (e.g., module versus system degradation). These choices may not have an equal impact on the final result, but we will display several rudimentary flowcharts to attempt to illustrate the complexity of the decision process. In the following figures, red rounded rectangles indicate input parameters such as data. Blue diamonds indicate decision points, and green rectangles illustrate processes or process outputs. Recommended default settings that were used in the Round 3 RdTools assessment are indicated by bold, underlined text wherever applicable.

Before the data can be evaluated, an initial data-quality assessment must be conducted, illustrated in Fig. 3. Some aspects of data quality are relatively unambiguous, e.g., ensuring proper time synchronization of separate data sources, or excluding unphysical erroneous data. Other decisions are less straightforward, leading to differences in analyst preference. For instance, nighttime data are often excluded, but this can be approached in several ways. Additionally, systems with high dc-to-ac power ratio can lead to "inverter clipping." Clipping occurs during the most productive days and times of the year, when the output is limited by the inverter. Clipping can mask degradation and may or may not be removed depending on the analyst's interest.

Whether to evaluate the entire available dataset or just a subset can depend on other choices in the decision tree. For example, linear regression methods have high leverage, indicating that they are sensitive to the beginning and ending of the seasonal cycle and should be evaluated only in full-year increments of data [10]. Missing data caused by maintenance events or sensor replacements, for example, can pose a challenge for the analyst, depending on the extent of the gap and the missing variables

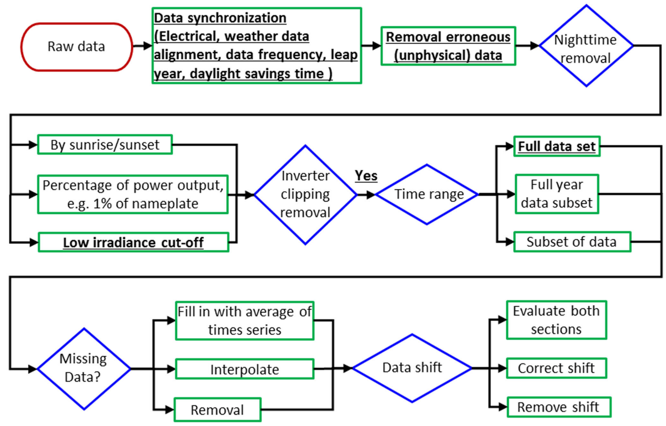

Fig. 3. Initial data-quality decision tree. The red rounded rectangle indicates the input parameter. The blue diamonds indicate decisions, and the green rectangles illustrate processes or process outputs. Default settings in RdTools are indicated by bold and underlined text.

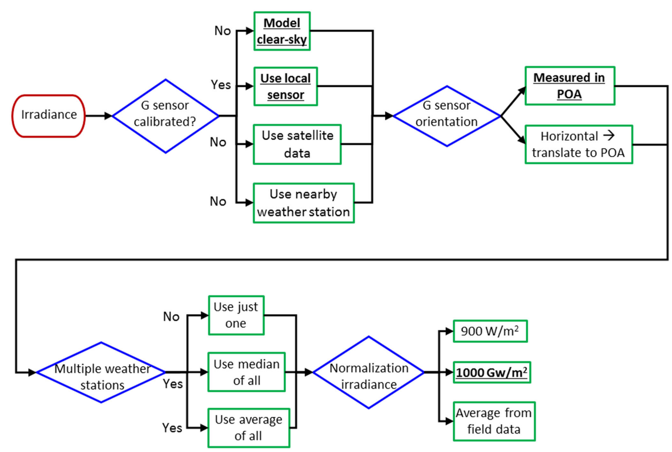

Fig. 4. Decision tree for the irradiance input data. The red rounded rectangle indicates the input parameter. The blue diamonds indicate decisions, and the green rectangles illustrate processes or process outputs. Default settings in RdTools are indicated by bold and underlined text.

in question [29]. Sections of missing data may be removed or filled in with various interpolation methods. If the shift is readily detectable, it can be corrected by an uncertainty minimization procedure [30]. Other ways to handle a data shift include running the analysis in two separate sections—before and after the data shift—or to eliminate the shifted data from consideration, particularly if the duration is short and is located at the end or start of a dataset. Start-up issues that typically get resolved within weeks or months of operation date are a common cause of data shifts.

Following general data-quality assessment, the second branch of the decision tree (see Fig. 4) pertains to how solar irradiance resource data are incorporated. The accuracy of the collected irradiance depends, in part, on the instrument and its calibration [31]. An uncalibrated instrument fielded for several years can bias the results substantially and is one of the most significant contributors to R_d uncertainty [32]. Frequent calibration is an accepted best practice, yet it often does not happen in practice. In

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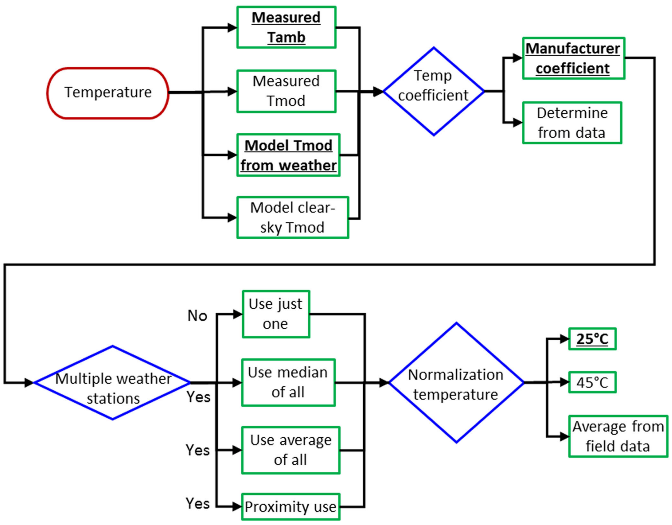

Fig. 5. Decision tree using the temperature data. The red rounded rectangle indicates the input parameter. The blue diamonds indicate decisions, and the green rectangles illustrate processes or process outputs. Default settings in RdTools are indicated by bold and underlined text.

the absence of calibrated ground-based local sensor data, other sources may be used such as the national solar radiation database (NSRDB), which uses a two-step physical model to calculate solar radiation from satellite data in its latest version [33]. Other strategies may encompass using empirical and semiempirical solar radiation datasets, modeled clear-sky data, or nearby weather stations [34]–[38]. Global horizontal irradiance measurements require transposition into POA irradiance, but several such translation methods exist, potentially impacting the results [39].

Larger plants may also use several weather stations; thus, a decision must be made on how to best use the different data streams. Finally, the reference conditions must be selected, which could be in accordance with standard test conditions (STC),[1] but alternative reference conditions may also be chosen [40]. Each step along the analysis pathway provides an opportunity for introducing errors and differences between analysts and analysis procedures.

Fig. 5 shows a decision tree for incorporating temperature into the analysis. Direct measurement of module temperature (Tmod) is preferred for normalizing PV performance data. However, Tmod measurements taken on the back of the module will often experience a slightly different temperature than the PV cell junction, leading to measurement offsets [41]. In addition, collecting consistent Tmod over several years or decades is very difficult because sensors often detach or malfunction after years in the field. Tmod can also be modeled in a variety of ways, typically by using Tamb and wind speed or in a clear-sky model [42]–[44].

Tmod coefficients also require a decision by analysts: to trust manufacturer-reported nameplate temperature coefficients, or to determine the temperature response directly from the collected

[1]STC: Irradiance = 1000 W/m², Air mass = 1.5, Module temperature = 25 °C.

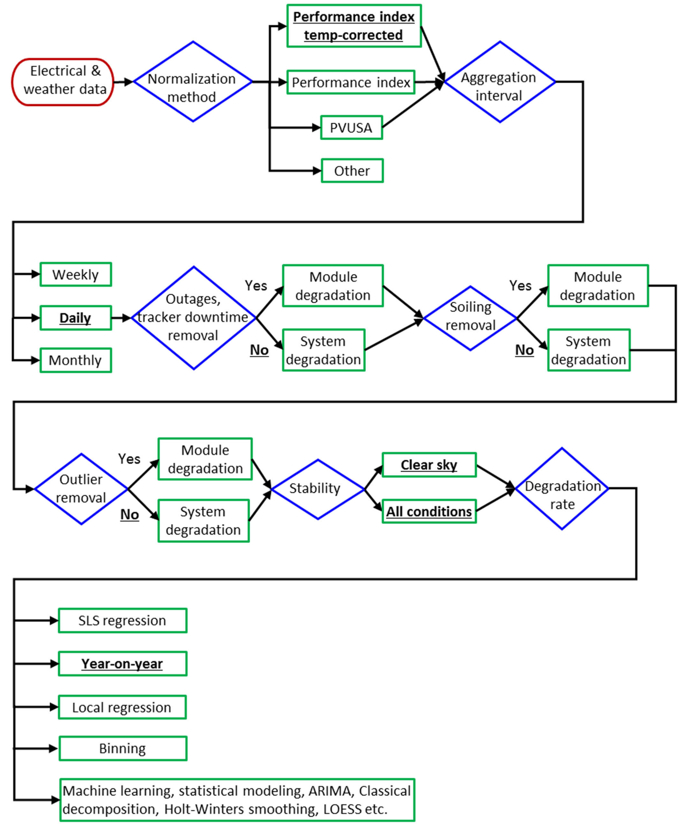

Fig. 6. Decision tree for the degradation rate calculations. The red rounded rectangle indicates the input parameter. The blue diamonds indicate decisions, and the green rectangles illustrate processes or process outputs. Default settings in RdTools are indicated by bold and underlined text.

data, as was considered in [23]. Care must be taken that the temperature coefficient is determined in the same filtered or binned data window as for power evaluation, and a choice must be made if multiple temperature channels are present. The reference comparison temperature must also be selected, often chosen at STC. However, STC conditions are a rather infrequent yearly occurrence for most of the world; therefore, an alternative temperature may be chosen more representative of the average annual temperature [40]. Additional considerations not discussed here may include corrections for angle of incidence [45] or for spectral effects [46].

The final decision tree for R_d calculations is complex and is only shown in its rudimentary form in Fig. 6. Typically for degradation analysis, data are first corrected for irradiance and temperature. Customarily, this may be the performance index in its temperature-corrected or nontemperature-corrected form [47]. Other methods such as the older PV for utility-scale application (PVUSA) method or a variant of it may be used [48]. If data are collected more frequently than daily (typical at the time of the writing: 1 min, 15 min, or hourly), then raw data may be aggregated into daily, weekly, or monthly intervals. These aggregation intervals are not a necessity and do not have to be adhered to, but they are commonly used. The decision tree becomes more subjective for outages or tracker downtime. If *module* degradation is the specified interest, then the downtime

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or outages are a temporary abnormality and may be removed to determine the typical performance. On the other hand, if the specified interest is *system* performance, then these temporary occurrences represent the overall system performance and may be included in the analysis—unless the interest is "nominal" system performance, in which case these temporary events may be excluded again. This discourse highlights the subjectivity of some of these decisions that are best handled with clear documentation of the goals and methods to be employed.

Soiling is very comparable in this respect, at least nonpermanent soiling. If the analyst's interest is in module performance, then seasonal soiling represents an intermittent state and may be removed. However, soiling represents a real loss of performance and should be included in calculations of overall system yield. Other similar sources of outliers include snow or shade, particularly if the system is affected while the sensor is not [49].

Finally, a method must be selected to extract a degradation rate from the normalized data. Some examples were considered in Section I, including linear regression, seasonal decomposition, or the year-on-year approach. The options available to PV analysts are growing all the time, particularly with recent advances in local regression, binning methods, and machine-learning algorithms [2], [13], [50], [51].

The decision trees depicted here are not intended to be comprehensive; yet, they provide a sense of the complexity of the decisions that an analyst must make. As demonstrated above, numerous opportunities exist for different analysts to choose—intentionally or otherwise—different paths through the performance and degradation analysis forest. Even neglecting the possibility of erroneously implementing particular steps, it is clear that without specific guidance for analysts, a wide range of results should be expected. The question is not *why* calculated degradation rates differ between analysts, but rather, why would they ever be expected to be the *same*?

IV. Conclusion

An interlaboratory study was conducted focused on the variability between analysts when the same PV performance data are evaluated. In the first round, no guidance was provided, resulting in a dramatic spread of results equivalent to 10% of lifetime energy yield. Providing written instructions, eliminated some outliers, but variability remained high. Finally, in using the free open-source software RdTools, we were able to reduce the variance between analysts by more than two orders of magnitude over their preferred but subjective methods. These encouraging results of more consistent PV system evaluations may also lead to increased confidence of investors in the performance of their assets. A deeper dive into the causes of analyst variability uncovered a great diversity of possible options available to the PV analyst, resulting in differing degradation outcomes.

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