Application of IEC 61724 Standards to Analyze PV System Performance in Different Climates

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***Abstract* — After a PV system is installed, periodic analysis is necessary to track how measured performance meets expectations. IEC 61724-3 outlines methods to quantify long term performance of PV systems. Applying these methods can be challenging due to the large quantity and possible quality control issues with measured data. In this paper, the methods outlined in IEC 61724-3 are applied to data collected at PV systems operating in different climates. The methods used to process data, run quality control tests, and compute performance metrics are described along with system performance issues found through the analysis.**

***Index Terms* — IEC 61724, open source software, system performance**

I. Introduction

The International Electrotechnical Commission (IEC) has developed guidance to measure and analyze energy production from photovoltaic (PV) systems. IEC 61724-1, -2, and -3 [1,2,3] outlines guidance on data collection and evaluation methods for short term capacity and long term system performance. This paper focuses on the energy evaluation outlined in IEC 61724-3. The evaluation compares measured energy production to expected energy production given site specific weather conditions and system specifications. The procedure evaluates system performance over a full range of environmental and operating conditions, generally over the course of one year.

The energy performance index (EPI), defined as the ratio between measured energy and expected energy, is recommended to track long term system health [3,4,5]. A system performance model, which can be simple or complex, is used to estimate expected energy. While small systems might use a simple performance ratio (PR) to model expected energy, this method is influenced by seasonal temperature variations. Even a temperature corrected PR can have variations which skew results due to seasons and geographic locations. More complex models, such as the Sandia PV Array Performance Model (SAPM) [6], System Advisor Model (SAM) [7], and PVsyst [8], take into account measured weather conditions along with estimates for soiling and degradation. EPI is computed for times when the system is available (in-service EPI) and over the entire year (all-in EPI). System availability is generally determined using inverter operation or other status indicators.

The guidelines outlined in IEC 61724-3 are designed to be flexible, allowing analysts and system operators to define a set of requirements to quantify performance for a particular system. The requirements can change depending on the system size, instrumentation, and intended purpose of the analysis. In general, a system performance model must be defined along with data filtering methods and thresholds used in data quality control tests. These decisions can have a large impact on the resulting analysis. For example, it is important to apply data quality control tests prior to running a performance model using measured data. Poor quality data, related to sensor or human error, must be properly filtered out when evaluating system performance. Small gaps in data can be filled using a variety of methods, including interpolation, using data from duplicate sensors, historical data, or data generated using models. However, larger data gaps might have to be eliminated from the performance analysis. Duplicate sensors can also be used to detect sensor drift or compute parameter variability. IEC 61724-3 includes example data filtering criteria to identify data that is outside expected range, missing, associated with a dead sensor, or changes abruptly. The filtering criteria should be adjusted according to site specific conditions and system instrumentation. After running a preliminary analysis, it is important to assess the model and other assumptions used to define system performance until the analyst and system operator agree on a final analysis procedure. These decisions can be challenging given the large amount of PV system data, systems that collect different types of data, and the wide range of possible data quality control issues.

This paper describes an application of the standards outlined in IEC 61724-3 using data collected at identical PV systems operating at four sites across the United States. Results are used to evaluate system performance and track how data quality control tests diagnose faults and system availability. The open source software packages Pecos [9] and PVLIB [10] are used for the analysis.

II. Data

The data used in this analysis was collected as part of the Regional Test Center (RTC) program managed by Sandia National Laboratories (SNL). The RTC program collects data at several sites across the United States, including Albuquerque, New Mexico; Orlando, Florida; Williston, Vermont; and Las Vegas, Nevada. Identical 'baseline' PV systems and weather stations were installed at each site (Fig. 1). These systems are used to test sensor operation and maintenance routines. Data collection is periodically disrupted due to planned site and system upgrades. For this reason, sensor failure and system downtime is expected to be higher for these systems, as

Fig. 1. PV system at the Nevada RTC site. Identical systems are located in New Mexico, Florida, and Vermont.

compared to production-level systems.

Each PV system is configured with two inverters, each with one series-connected string of 12 Suniva Optimus 270 Black modules. These modules have the following datasheet electrical characteristics: Pmax = 270 W, Vmp = 31.2 V, Voc = 38.5 V, Imp = 8.68 A, Isc = 9.15 A. The arrays all face South and are tilted at 35˚.

The weather station collects data for global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), wind speed, wind direction, air pressure, and relative humidity. For each string, DC voltage, DC current, AC voltage, AC current, AC power, power factor, frequency, reference cell irradiance, and reference cell temperature are recorded. Module temperature is recorded at 8 locations per string. Ambient temperature and POA irradiance is also recorded at the site. Data collected in 2016 was used for the analysis. Data was recorded at a 1-minute time interval, resulting in approximately 25 million data points per site.

III. METHODS

The following section describes an application of IEC 61724-3 to compute system performance at the four sites. The analysis is carried out using Pecos [9] and PVLIB [10], both open source software packages developed by SNL.

Pecos is used to analyze the quality of time series data, subject to a set of quality control tests. Many of the features included in Pecos were designed specifically for quality control tests outlined in IEC 61724-3, including the ability to identify data that is outside expected range, missing, associated with a dead sensor, or changes abruptly. Additionally, Pecos includes methods to use filters and composite signals in the analysis. Filters can be used to smooth data and/or eliminate data collected at specific times from quality control tests. Composite signals are any type of new data generated using existing data or models. Composite signals can be used to include performance models or simple relationships in the analysis.

Time series data can be easily loaded into Pecos from a wide range of formats, including from file (i.e. csv, excel) and directly from databases (i.e. SQL). For this analysis, a years' worth of data is loaded into Pecos for each site. Similar analysis could be run in real-time (or near real-time) to help diagnose system performance issues quickly. Daily analysis is recommended to ensure systems record high quality data. Yearly summary reports can then be performed to track long term system health. Pecos can be installed from https://github.com/sandialabs/pecos.

PVLIB is used to model expected system performance based on measured weather conditions and to compute a data filter based on sun position. Several performance models are included in PVLIB, including the SAPM [6], single diode model [11], and PVWatts model [12]. PVLIB can be installed from https://github.com/pvlib/pvlib-python.

The following steps are taken to analyze energy production for each site:

Step 1: Check for timestamp issues. When working with time series data, it is important to check for and fix timestamp issues before proceeding with analysis. Pecos includes methods to check for missing timestamps, duplicate timestamps, and timestamps out of sequence. These methods correct issues with the timestamp and record issues in the final report.

Step 2: Preliminary data inspection: Visual inspection of sensor data can help quickly identify systematic errors, and define filters and quality control tests. Sensor data plotted as a time-of-day versus day-of-year heatmap can help identify shading issues, large data gaps, and upper and lower bounds for quality control tests. An example heatmap is shown in Fig. 2. This figure shows POA irradiance at the Nevada site. No persistent shading issues were noted based on the image and missing data is observed in February and November (vertical white lines). Pecos includes methods to create time-of-day versus day-of-year heatmaps with superimposed time series that show sun position or other attributes.

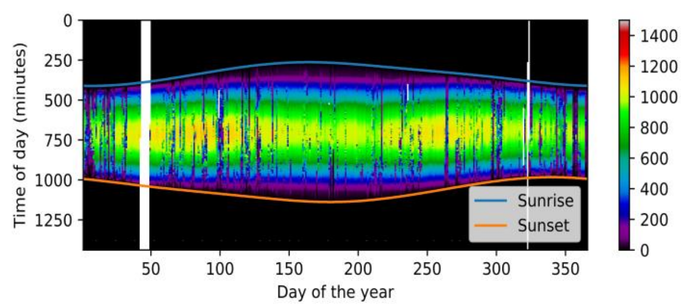

Fig. 2. POA irradiance heatmap for the Nevada site.

Step 3: Apply filters. Data collected at night or during low irradiance conditions can introduce errors in the performance evaluation. For this reason, data that is collected when the sun elevation is less than 20 degrees is eliminated from the analysis. PVLIB is used to compute sun position as a function of site location and date-time. Additional low irradiance filters could be added in future analysis.

Step 4: Add composite signals. Computing relationships between different types of measured data and comparing measured data to models can help identify issues with system performance. The following composite signals are used in the analysis: 1) DC power computed from DC voltage and DC current, 2) inverter efficiency computed from AC and DC power, 3) normalized efficiency computed from DC power and POA irradiance, and 4) module temperature deviation defined as the difference between each module temperature sensor and the median value over all 16 module temperature sensors. When multiple sensors are available, comparing a single sensor to the median value can help identify sensor drift. An additional composite signal, the power performance index, is computed in Step 6. These composite signals are used in quality control tests to check for anomalous conditions.

Step 5: Run data quality control analysis. IEC 61724-3 outlines basic quality control tests to check if data is outside expected range, missing, associated with a dead sensor, or changes abruptly. The methods in Pecos were designed to run these tests. For this analysis, data that is missing for less than 2 hours was filled using a linear filter. Data that is missing for more than 2 hours is flagged as missing. A sensor is flagged as recoding data outside an expected range if the threshold specified in Table I (column 2) is surpassed for more than 2 consecutive hours. The thresholds for air pressure are based on expected air pressure, calculated from site elevation using PVLIB. A sensor is flagged as dead if it changed by less than

TABLE I
Expected range and threshold values for quality control tests.

Variable	Expected range	Dead sensor threshold	Abrupt change threshold
DC current and AC current (A)	> 0 and < Imp·1.5	< 0.0001	
DC voltage (V)	> 0 and < Vmp·N·1.2 *	< 0.0001	
AC voltage (V)	> 230 and < 250	< 0.0001	
DC power ** and AC power (W)	> 0 and < Pmp·N·1.2 *	< 0.0001	
Power factor	> -1 and < 1	< 0.0001	
Frequency (Hz)	> 57 and < 63	< 0.0001	
POA, DNI, GHI, and ref cell irradiance (W/m^2)	> -6 and < 1500	< 0.0001	
DHI (W/m^2)	> -6 and < 500	< 0.0001	
Wind speed (m/s)	> 0 and < 32	< 0.0001	
Wind direction	> 0 and < 360	< 0.0001	
Air pressure (mbar)	> P·0.97 and < P·1.03 *	< 0.0001	> 25
Relative humidity	> 0 and < 100	< 0.0001	> 50
Ambient temperature (ºC)	> -30 and < 50	< 0.0001	> 20
Module and ref cell temperature (ºC)	> -30 and < 90	< 0.0001	> 20
Inverter efficiency**	> 0.5 and < 1		> 0.25
Normalized efficiency **	> 0.8 and < 1.2		> 0.25
Module temperature deviation (ºC) **	> -10 and < 10		
Power performance index **	> 0.8 and < 1.2		

* N is the number of series connected modules and P is the expected air pressure based on site elevation
** Composite signal

the threshold specified in Table I (column 3) for 5 consecutive hours. A sensor is flagged as changing abruptly if the value changes by more than the threshold specified in Table I (column 4) in a 15-minute timeframe. These thresholds can be adjusted to customize analysis. For each test failure, the sensor name, along with the start and end time of each failure, and an error flag is recorded in the final report.

Step 6: Compute expected power and energy production. Expected energy is computed using actual weather data. If weather data is unavailable, or is deemed unreliable given one or more quality control tests run in Step 5, it is eliminated from the energy calculation. The PVWatts DC model [12] is used to compute expected DC power; the model was run using PVLIB. Expected DC power is then converted to energy output. An additional quality control test is defined to flag times when the power performance index, defined as measured power divided by expected power, is outside an expected range of 0.8 to 1.2 for more than 2 consecutive hours. As with the quality control tests run in Step 5, test failures associated with the power performance index are recorded in the final report.

Step 7: Compute metrics. IEC 61724-3 recommends computing in-service EPI and all-in EPI. For this analysis, several additional metrics were computed, including data availability (DA), quality control index (QCI), and system availability (SA). For each sample time, DA is the percent of expected data that is recorded and QCI is the percent of available data that passed all quality control tests. The systems used in this analysis do not include an inverter status flag that indicate when the system is available. For that reason, SA is based on the results of quality control tests associated with power (AC and DC), inverter efficiency, normalized efficiency, and power performance index. For each sample time, SA is 1 if the quality control tests associated with these parameters all pass and 0 otherwise. In-service EPI is the ratio between measured energy and expected energy, computed when the system is available. All-in EPI is the same ratio, computed over the entire year. SA, in-service EPI, and all-in EPI are computed for each string. If data is missing while the system is known to be available, energy estimates could be made using historical weather data during that time.

After completing these steps, the analyst and system operator should review quality control test failures and performance metrics. Adjustments can be made to the quality control thresholds and performance model if significant issues are identified, otherwise, the analysis should remain stable year-to-year. Changes in the analysis should be clearly documented. The thresholds and model input can be saved in Python scripts that are used to run Pecos and PVLIB. These scripts can then be rerun to reproduce results and for future analysis. It is noted that several procedures recommended in IEC 61724-3 were not included in this analysis. For example, historical data was not used to compute predicted energy, systematic (bias) and random (precision) uncertainties were not analyzed, cleaning and calibration schedules along with grid availability was not included in the analysis, and missing or erroneous data was not replaced with data from other sources. These steps could be included in future analysis.

IV. Results

The RTC data was analyzed using the methods outlined above. Preliminary analysis, run on a daily basis, indicated that modules at all sites were underperforming by approximately 5%. This prompted a module flashtest at the New Mexico site. The electrical characteristics were subsequently updated to the following: Pmax = 255.7 W, Vmp = 30.9 V, Voc = 38.0 V, Imp = 8.28 A, Isc = 8.74 A. The discrepancy with datasheet values could be caused by light induced degradation or overrating. The new values were used to estimate performance for the year.

For each site, time-of-day versus day-of-year heatmaps were generated for each sensor reading. These figures were used to identify shading issues, large data gaps, and define thresholds listed in Table 1. No persistent shading issues were observed. A large gap in the data record was noted in Vermont between the middle of April and early May. Other data gaps were relatively short (a few days or less). Missing data was attributed to sensor failure, system maintenance, and data transfer issues.

Table II includes annual average data availability (DA), quality control index (QCI), system availability per string (SA), along with measured energy, expected energy, in-service EPI, and all-in EPI for each site. Fig. 3 and 4 illustrate DA, QCI, SA, in-service EPI, and all-in EPI throughout the year for the Nevada and Vermont site. DA, QCI, and SA are reported as a daily average. In-service and all-in EPI are reported as a monthly average.

DA was relatively high at all four sites with a few exceptions. In Florida, data was missing periodically, mainly between the middle of June and early October. As mentioned above, the Vermont site had a large gap in the data record, most of the data was missing over a 23-day period in the Spring.

QCI was also relatively high at all four sites. Note that QCI can be greater than DA because it is the percent of available data that passed all quality control tests. For example, at the

TABLE II
Annual DA, QCI, SA (per string), measured energy, expected energy production, and EPI.

	NM	NV	FL	VT
DA	99%	98%	96%	95%
QCI	98%	99%	98%	92%
SA, String 1	98%	86%	83%	72%
SA, String 2	98%	97%	84%	72%
In-service measured energy (kWh)	11517	10476	8693	5528
In-service expected energy (kWh)	11608	10679	9104	5802
All-in expected energy (kWh)	11696	11390	9911	7305
In-service EPI	99%	98%	95%	95%
All-in EPI	98%	92%	88%	76%

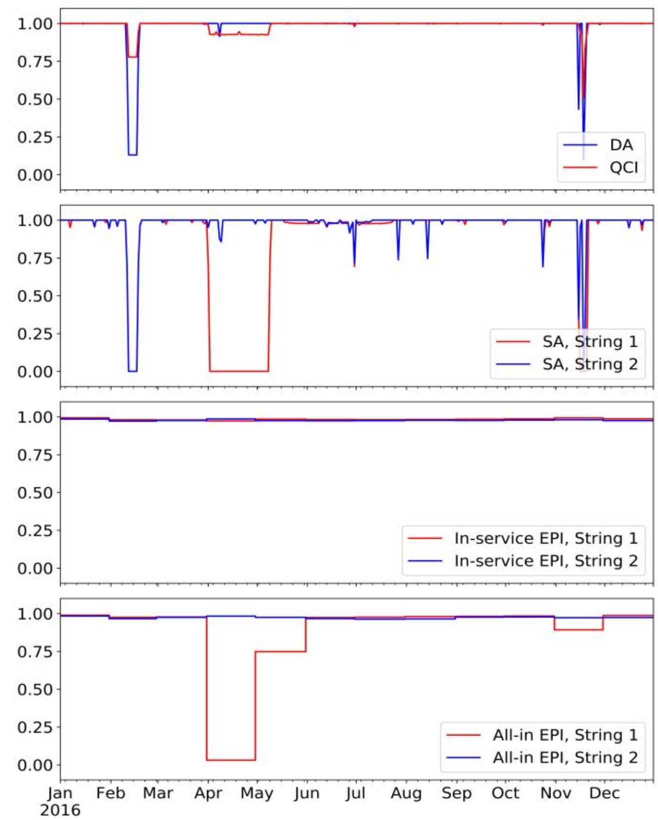

Fig. 3. DA, QCI, SA, in-service and all-in EPI for Nevada.

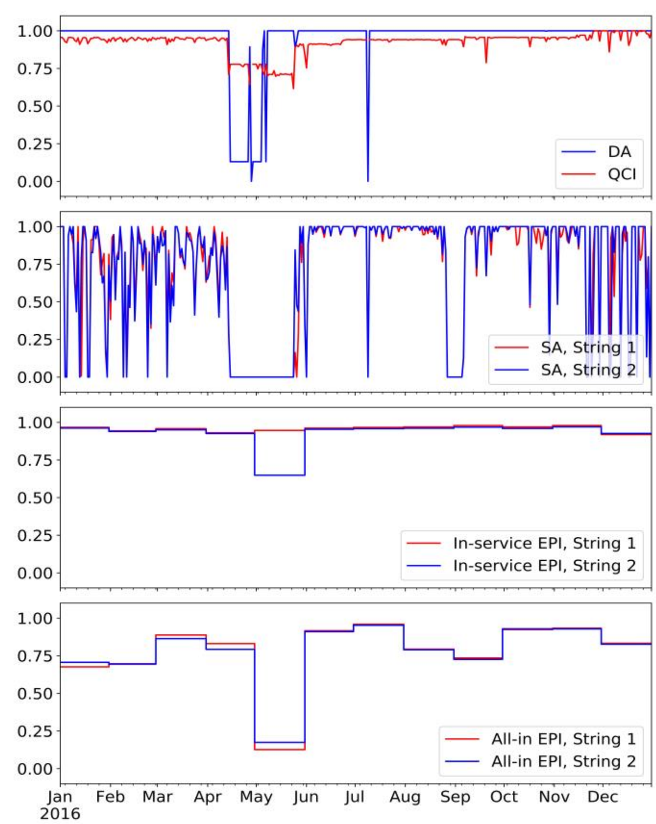

Fig. 4. DA, QCI, SA, in-service and all-in EPI for Vermont.

Nevada site, only 13% of the data was available between Feb 12 and Feb 17. Of the data that is available, 78% passed all quality control tests. During that time, DC current sensors were flagged as dead, with readings that changed by less than 0.0001 over 5 consecutive hours. At the Vermont site, QCI is consistently around 95% due to unexpected abrupt changes in normalized efficiency and a module temperature sensor that is out of alignment with other module temperature sensors. In April and May, QCI decreases to around 75% due to DC power and current readings that are below 0 and several other sensors that were flagged as dead. These issues were verified with system operators.

The system is defined as 'available' if sensor data associated with power (AC and DC), inverter efficiency, normalized efficiency, and power performance index pass all quality control tests. Using this definition, SA is reported per string. All sites, with the exception of Nevada, have very similar availability per string. In Nevada, String 1 DC power is very close to 0 between April 1 and May 9. The quality control test for DC power will not flag this as an error, however bounds on normalized efficiency, inverter efficiency, and the power performance index all indicate anomalous conditions during that time. In Vermont, SA is highly variable in the winter due to anomalous conditions in normalized efficiency, inverter efficiency, and power performance index. SA at the Florida site was similarly noisy, due to occasional low inverter efficiency.

In service EPI and all-in EPI were computed using measured and expected energy. In New Mexico, in-service and all-in EPI are both very high. In Nevada, Florida, and Vermont, in -service EPI is slightly lower and issues with system availability reduced the all-in EPI by 6 to 20%.

As part of this analysis, quality control tests identified numerous issues throughout the year at all four sites. The tests were able to accurately identify dead sensors, sensor drift, and underperforming inverters. Pecos keeps a record of the sensor name, start and end time of each test failure, and an error flag. This information can be included in HTML formatted reports, saved to a file, or stored in a database. Graphics can be generated which help pinpoint the data points that were involved in an individual test failure. Examples are shown in Fig. 5. Each example shows one day of data along with issues found using the quality control tests run as part of this analysis. The gray region indicates times when sun elevation is < 20 degrees. This region is eliminated from quality control tests. Green marks identify data points that were flagged as changing abruptly, red marks identify data points that were outside expected range. The top image shows a spike in normalized efficiency at the New Mexico site. The middle image shows a sudden drop in inverter efficiency at the Nevada site. The bottom image shows a module temperature sensor that is oscillating between normal and anomalous conditions at the Florida site.

If a quality control test results in false positives, thresholds and moving windows can be adjusted, filters used to eliminate data from quality control tests can be modified, the minimum number of consecutive failures needed to signal a warning can be increased, and data can be smoothed before the quality control test is run.

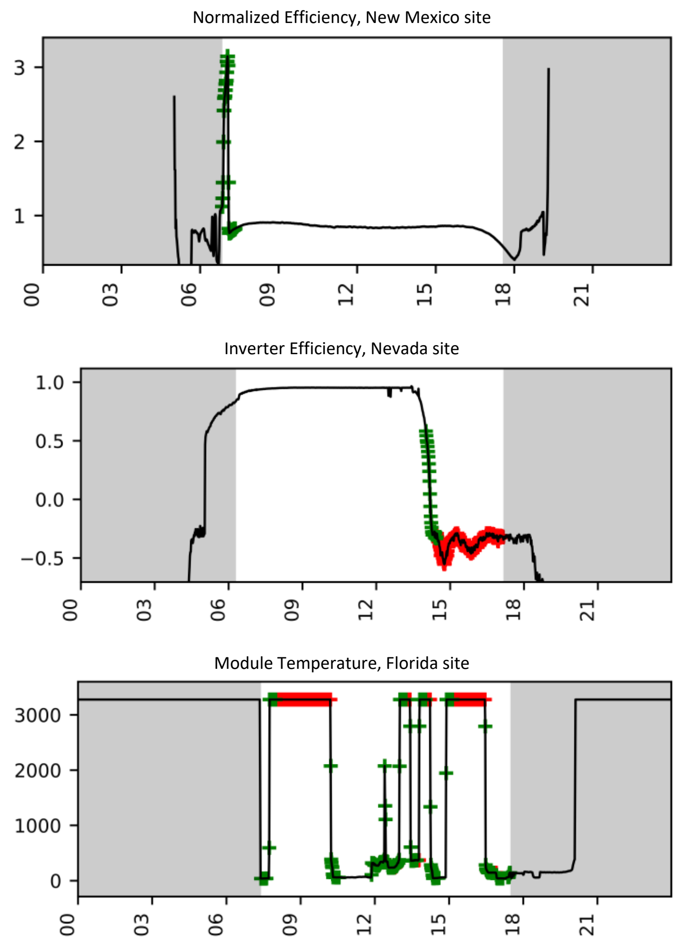

Fig. 5. Example quality control graphics illustrating quality control issues. Green marks indicate data points that were flagged as changing abruptly, red marks indicate data points that were outside expected bounds. The x-axis is in hours of the day.

V. Discussion

System performance was evaluated at identical PV systems operating at four sites across the United State using methods outlined in IEC 61724-3. Pecos and PVLIB, both open source software tools, were used to run the analysis. These tools were used to process and filter large quantities of data, run quality control tests, compute expected energy production and system performance, and generate reports and graphics. The Python scripts used to run the analysis can be used to reproduce results and to compare year-to-year performance.

The methodology was able to identify gaps in the data record and anomalous conditions. Thresholds used in the quality control tests were systematically adjusted based on discussions with system operators and visual inspection of system data. Future research will compare the method used to estimate data availability, quality control index, and system availability with system logs. While the methods result in similar analysis across the four sites, several factors, such as variable system availability in Florida and Vermont, require further investigation. In addition to the yearly performance evaluation discussed in the paper, short term capacity tests and daily quality control analysis are recommended to evaluate performance, minimize downtime, and ensure the collection of high quality data.

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