Received: 14 December 2021 | Revised: 25 February 2022 | Accepted: 12 April 2022

DOI: 10.1002/pip.3566

RESEARCH ARTICLE

PROGRESS IN PHOTOVOLTAICS WILEY

Photovoltaic fleet degradation insights

Dirk C. Jordan | **Kevin Anderson** | **Kirsten Perry** | **Matthew Muller** | **Michael Deceglie** | **Robert White** | **Chris Deline**

Renewable Energy Laboratory (NREL), Golden, Colorado, USA

Correspondence
Dirk C. Jordan, Renewable Energy Laboratory (NREL), 15013 Denver West Parkway, Golden, CO 80401, USA.
Email: dirk.jordan@nrel.gov

Funding information
Solar Energy Technologies Office (SETO), Grant/Award Number: 30295; U.S. Department of Energy (Office of Science, Office of Basic Energy Sciences and Energy Efficiency and Renewable Energy, Solar Energy Technology Program), Grant/Award Number: DE-AC36-08GO28308

Abstract

In the PV Fleet Performance Data Initiative, high-frequency data from commercial and utility-scale photovoltaic (PV) systems have been collected to examine performance loss rates (PLRs) at a fleet scale. To date, performance data from more than 7.2-gigawatt (GW) capacity, 1700 sites and 19,000 inverters—approximately equivalent to 6% to 7% of the entire US PV market—have been collected. An overall PLR of −0.75%/year was found, which is in line with historical and recent findings. Tracked silicon (Si) and cadmium telluride (CdTe) performed comparably with all fixed-tilt systems. Higher PLRs were found for hotter temperature zones; cooler climates exhibit a median −0.48%/year loss, which increases to −0.88%/year in hotter climates. High-efficiency module technologies showed median PLRs in line with conventional Si technologies but demonstrated markedly different PLR behavior when filtered only for low-light conditions <600 W/m^2. Causes for this technology-dependent behavior are under investigation.

KEYWORDS

degradation rates, durability, outdoor testing, performance, photovoltaic modules, photovoltaic systems, reliability

1 | INTRODUCTION

Utility-scale photovoltaic (PV) net generation across the United States exceeded 3% in June of 2021 with higher penetration in certain locales, for example, California exceeding 20% during the same time.[1] With PV rapidly increasing its share of generation, dependable electricity production is of utmost importance especially in an age of more extreme weather events. Accurately assessing the extent of PV performance loss over the lifetime of a plant helps to highlight reliability and durability deficits. Most components and products gradually lose their functionality over time consistent with the second law of thermodynamics.[2] For PV modules and systems, this gradual loss over the intended lifetime is typically very small compared with diurnal and seasonal fluctuations. However, the small relative size is financially magnified by (1) the size of the system, (2) the number of systems, and (3) the long-expected lifetime of 25–30 years. Reducing the size of this gradual loss leads to increased net present value and increased lifetime.[3] Moreover, warranty validation is very important, as more module manufacturers are adopting warranties based on the gradual performance loss. In addition, understanding the mechanisms behind the observed degradation will provide insights for improved future products. Therefore, correctly quantifying performance loss over time is an integral part of accurate and dependable electricity generation for current and future PV generations. Some of the authors have provided a summary of published literature on the topic of performance loss rates (PLRs) to provide a guideline to the community.[4] Other prior summaries of failures, typically characterized by sudden performance loss, have also been published for a large fleet of 100,000 systems; however degradation effects could not be assessed because only 5 years of annual performance data were available.[5]

Valuable insights from literature can be glimpsed, but the investigated products tend to be older and the variety in technology and location may be limited. Investigations of a large number of modules and systems providing a general overview of the state of the industry in a particular location are difficult to do but have seen an increased interest.[6–9] Because it takes several years to accumulate high-quality data, it is important to remember that studies on PLRs or curves only provide a temporary glimpse into the state of systems and may be subject to change. In this study, we use the large database from the PV Fleet initiative to investigate performance loss for thousands of systems across the United States and provide insights to PV stakeholders.

2 | PV FLEET INITIATIVE

In the PV Fleet initiative, high-frequency data are aggregated into one database to provide PV plant owners, operators, analysts, and researchers an opportunity to study PV performance on a large scale across the United States, as shown in Figure 1. The most common data frequency of the entire database is 15-min intervals with the data frequency extremes extending for some systems from 1- to 60-min intervals. The effort is distinctive because of the large number of systems; more than 1700 sites, with approximately 19,000 individual inverter data streams, provide a high-level perspective of PV systems performance. The total monitored capacity has surpassed 7.2 gigawatts (GW) or between 6% and 7% of the entire installed capacity in the United States[10] depicted in Figure 1. In addition, the fleet consists of primarily large-scale commercial and utility-scale systems with an average size of 4.1 megawatts (MW) and nonresidential systems, which may have different performance and reliability challenges.[11] The majority of the systems fall between 100 kilowatt (kW) and 1 megawatt (MW) with long tail extending above 100 MW and shorter tail towards 10 kW. The technology breakdown in the pie chart of Figure 1B illustrates a majority in crystalline silicon (c-Si) PV with a small percentage of thin-film technology, mostly cadmium telluride (CdTe)-based modules. Additionally, more than 20% consists of high-efficiency technologies such as passivated emitter and rear cell (PERC) and n-type technologies that the industry is increasingly adopting.[12]

As suggested by the broad geographic distribution in Figure 1B, the fleet covers a range of climate types. Rather than displaying the well-known, but agriculture-focused Köppen–Geiger climate classification, we show instead the PV-specific temperature zones (rack) of Karin et al.[13] Temperature and humidity are two main drivers of PV performance and loss, although other environmental factors such as wind, thermal cycling, irradiance and ultraviolet light in particular are important too.[14] The equivalent temperature zone represents an Arrhenius-weighted equivalent temperature, and the humidity zones are based on the specific humidity. Higher numbers represent hotter and more humid regions, respectively. The composition of this dataset with respect to PV-specific climate zones is shown in Table 1, along with the broader US fleet as represented by the April 2020 utility-scale power plant database from the US Energy Information Administration.[15] In general, we have close but not exact match to the broader US fleet by climate zone.

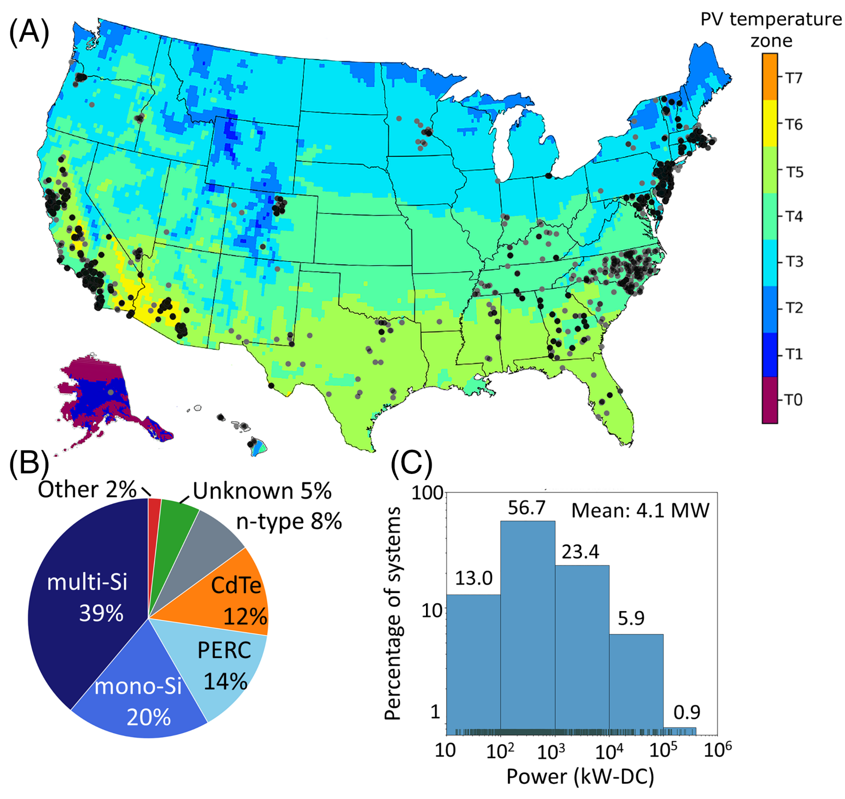

FIGURE 1 (A) Geographical distribution of the PV systems considered here (gray dots, turning black with collocated sites) with color-coded PV-specific temperature zones (rack) in the United States. (B) Technology pie chart by number of inverters and (C) system size distribution

TABLE 1 PV climate zone comparison between the broader US PV fleet (second column) and systems studied here in the PV Fleet initiative (third column)

PV climate zone label (temperature/humidity)	Power plants USA (%)	PV Fleet (%)
T2:H2	0.2	0
T3:H2	1	0.6
T4:H2	0.5	0
T5:H2	0.1	0
T6:H2	0	0
T3:H3	0.1	0
T4:H3	2.1	0.6
T5:H3	3.5	4.8
T6:H3	2.8	1.6
T7:H3	0.9	5.1
T3:H4	0.9	0
T4:H4	35.7	34.6
T5:H4	35.4	34.5
T6:H4	7.8	12.8
T7:H4	0.5	3.4
T5:H5	2.8	0.8
T6:H5	5.6	1.1

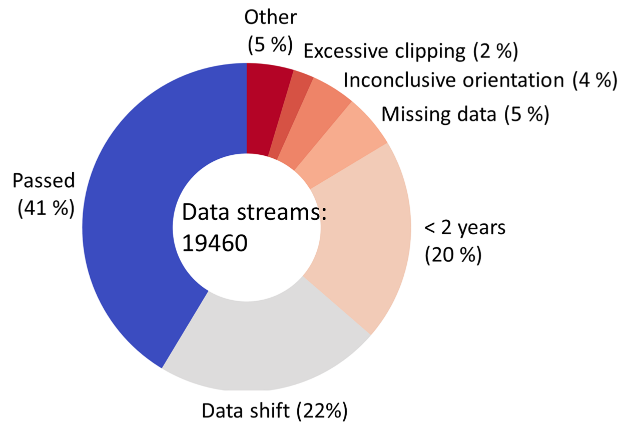

FIGURE 2 Data quality assurance chart of various anomalies of inverter time series passing or affected by a quality issues

3 | METHOD AND DATA QUALITY ASSURANCE

With a dataset of this size, automatic data quality assurance (QA) routines are essential to obtain accurate information. Data quality outcomes for each data stream in the fleet are shown in Figure 2, tabulated by anomaly type. PLRs can be particularly influenced by nonphysical shifts in the observed quantities such as power, irradiance, or temperature and in time. This can be caused by sensor issues (replacement, misalignment, and drift) or computer error (time zone or scale change). Changepoint detection routines are used to detect data shifts and automatically correct time shifts in individual inverter and energy meter data streams. Data shifts in observables are partitioned into sections where only the longest continuously passing time period is retained and used for further analysis. Future QA versions could potentially include automated correction to shifts in the observables[16,17] which should increase the percentage of passing systems.

Data shifts were the most common reason for rejection of a data stream, followed by systems with less than 2 years of normalized performance data—the minimum requirement for using the year-on-year methodology in RdTools.[18,19] Missing data are the next highest category; data streams are rejected if they contain a substantial percentage of data gaps (>25% of daytime data) because of the resulting inflated uncertainty in PLR.[20] Sometimes, metadata such as the orientation of the system was inaccurate leading to erroneous performance projections. We employ unsupervised machine learning routines to determine system orientation more accurately, with additional manual validation before applying any azimuth modifications.[21] Higher direct current (DC)-to-alternating current (AC) ratios or inverter loading ratios have become more common, which causes the inverter to limit the output of the system. This phenomenon is referred to as "clipping," as the daily power output curve appears to be trimmed during the most productive days. Because excessively high DC-to-AC ratios can mask underlying degradation trends, we reject data streams where more than 10% of the points are clipped. Even after passing the data QA, approximately 10% of inverter data streams were erroneously influenced by data issues, specifically data shifts. In this case, the normalized performance traces for three analysis methods in RdTools were examined to find the best PLR not affected by data shifts. The three analysis types are discussed in detail below.

Accepted data were then analyzed to estimate PLR. Typically, PLR is understood to quantify the total recoverable (e.g., operational) and nonrecoverable losses.[22] In this study, we use the term to refer to DC and AC subsystem degradation where a negative value constitutes a loss. Compared with a naïve approach, data are initially filtered to remove the impact of outages and clipping prior to extracting a PLR. Outages would generally increase performance loss, while clipping can obfuscate module and DC-side degradation. The analysis methods used here have been previously described and are available open-source in RdTools.[19] Briefly, the workflow begins by normalizing the raw inverter energy to the expected energy based on irradiance and module temperature. The data are then filtered to remove outages, plane of array irradiance outside of 200–1200 W/m^2, anomalous temperature outside the range -50°C to 110°C, and times of clipping using a geometric (i.e., logic-based) clipping filter.[23] After filtering, data are aggregated daily, and the RdTools year-on-year method is used to estimate annual degradation. Except where specifically noted, we use AC power or energy in this study.

The three common normalization methods of the PV performance data used in RdTools are (1) local irradiance and temperature sensors, (2) satellite irradiance and data from the National Solar Radiation Database (NSRDB), and finally, (3) modeled irradiance under detected clearsky time periods.[24] Each method has distinct advantages and disadvantages. The most precise method is to use locally sited sensors after passing aforementioned quality checks. However, physical sensors can be prone to drift and measurement bias if not regularly cleaned and calibrated. In addition, some systems are not equipped with local sensors, necessitating one of the other two normalization methods. In the clearsky model method, consistent annual environmental conditions are assumed; thus, real environmental trends such as pollution from nearby wildfire can unintentionally bias PLR results. Modeled clearsky assumptions are reasonable for systems with over 5 years of performance data, but the method tends to be less accurate over shorter time periods.[25] Using satellite irradiance data avoids the local sensor susceptibility to drift and real environmental changes over short time periods. However, the accuracy over short time periods is also not ideal for PLR assessment, particularly since all-sky conditions are considered.[25] We therefore stick to sensor-based analysis where possible. Indeed, we determined 73% of PLRs using the sensor method, with only 22% and 5% of PLRs determined with the NSRDB and clearsky methods, respectively. Measured back-of-module temperature is preferred for the sensor and clearsky methods when available; in cases with no measured module temperature data passing QA (29% of sensor PLRs, 15% of clearsky PLRs), modeled values based on ambient conditions are substituted. NSRDB PLRs all use modeled module temperature for the normalization. Two-sigma confidence intervals are also calculated, with uncertainty generally decreasing with increasing data length. The confidence interval assumes a critical role, as further fleet-scale analyses are weighted by the inverse of the confidence interval. Therefore, more weight is given to PLRs with small confidence intervals. This allows trends to be distilled even if some PLRs happen to be contaminated by latent data problems.

Finally, it is important to disclose how the data for this study were obtained, because this apparently ordinary detail can have considerable impact on the presented results. Large studies can easily but unintentionally be biased if the investigated sample is not representative of the overall population. In general, we may not know the performance of all PV systems at large, but the intent is to obtain a stratified sample, representative of climates, mounting configurations, technologies, and so on. It is important to note that the systems included here were not randomly selected and as such latent unintentional bias could still exist in our database. We attempt to minimize unintended bias by engaging with multiple PV fleet owners and collecting their entire fleet of data (not just a few problematic or well-performing systems). This may not eliminate bias, but it should help to minimize it. As more partners and systems are added to our database, that bias should diminish over time. We will also work to assess and reduce any bias introduced by our automated data QA process (if any).

4 | DEGRADATION DISTRIBUTION

The aggregated PLR distribution from the entire fleet is displayed in blue in Figure 3 with a histogram of individual inverter-level PLRs. Median PLR for the fleet is −0.75%/year based on 4915 inverters passing automated data quality checks. The left skew of Figure 3 resembles other distributions occurring in the reliability sciences and is approximated by a Gumbel or extreme value distribution.[26] A second histogram is shown in red displaying previously published literature values of module-level and system-level degradation values from our 2016 degradation summary paper.[27] These previously published literature values used "high-quality" data, that is, studies in which two or more measurements were used to determine the PLR. The data making up our fleet-level histogram are available for download, along with some nonattributable system configuration details.[28]

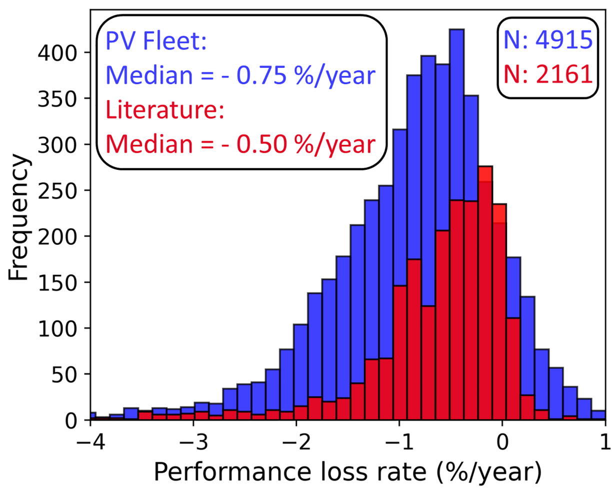

FIGURE 3 Performance loss rate distribution for the PV Fleet initiative (blue) compared with values aggregated from high-quality values (two or more measurements) from the literature (red)

While our current analysis is based on system PLR, the smaller median PLR of −0.5%/year for the previously published results may be attributable to the different composition of measurements, predominantly (∼80%) based on module-level measurements rather than system PLRs. In contrast to the current work, which is based on continuous high-frequency production data for systems, the previous distribution contained only 24% of data points based on continuous data, 42% were based on discrete IV curve measurements, with in some

TABLE 2 Weighted performance loss rate statistics for the PV Fleet database compared with high-quality (greater than or equal to two measurements)

Type	Median (%/year)	Mean (%/year)	P90	Data points
Inverters	−0.75	−0.88	−1.90	4915
Sites	−0.68	−0.86	−1.73	585
Literature (≥2 data pts)	−0.50	−0.70	−1.40	2161

Note: The P90 is the PLR value above which 90% of all systems fall.

cases as few as two measurements (34%). Compared with module-only measurements, system-level PLR (as determined from inverters or site interconnect energy meters) also include other degradation or recoverable losses such as availability, soiling, and snow. Table 2 provides additional summary statistics for inverter, site, and literature distributions. The site distribution is obtained as the median PLR at each site, that is, taking the median over multiple inverter PLRs. Compared with the inverter-level median, this is only slightly smaller at −0.68%/year. P90 values, which serve as cutoff points that 90% of all systems outperform, are also given. The median and the P90 values are unaffected by our weighting by confidence interval, but the mean values are shifted immaterially by 0.01%/year to a higher PLR because of a left skew of the distribution, that is, fewer weights with high values. The median value of −0.75%/year is important because it is within the warranty level of a typical 25-year linear warranty used in the last 10 years. (Although with more stringent warranties being introduced, it will be interesting to see whether this remains true in the future.)

When comparing with other published studies, our median findings are in good agreement with a recent large study on residential systems in Europe[9] and 200 commercial-scale European systems from 2020.[29] On the other hand, the value is substantially smaller than a recent utility-scale study in the United States.[30] However, the data frequency for the study of Bolinger et al.[30] was predominantly monthly performance data making it difficult to account for all recoverable losses through operations and maintenance practices. In contrast, this study used high-frequency data, allowing for better distinction between outages and long-term performance loss.

5 | AC AND DC PERFORMANCE LOSS

Most sites more frequently contained AC data than DC data. When both AC and DC data streams for the same inverter were present, PLRs for both were obtained and compared. The difference between AC and DC PLR is centered on zero, indicating that changes in inverter performance over time does not generally contribute to system PLR. This is shown in Figure 4A, and this finding is supported by other recent publications.[31] However, the general trend obscures manufacturer and technology-specific tendencies. The cumulative distribution function (CDF) of Figure 4B shows that for most inverter manufacturers and technologies, the difference is close to zero. However, the central inverters of Manufacturer 1 show an added inverter degradation component to the overall system PLR. Unfortunately,

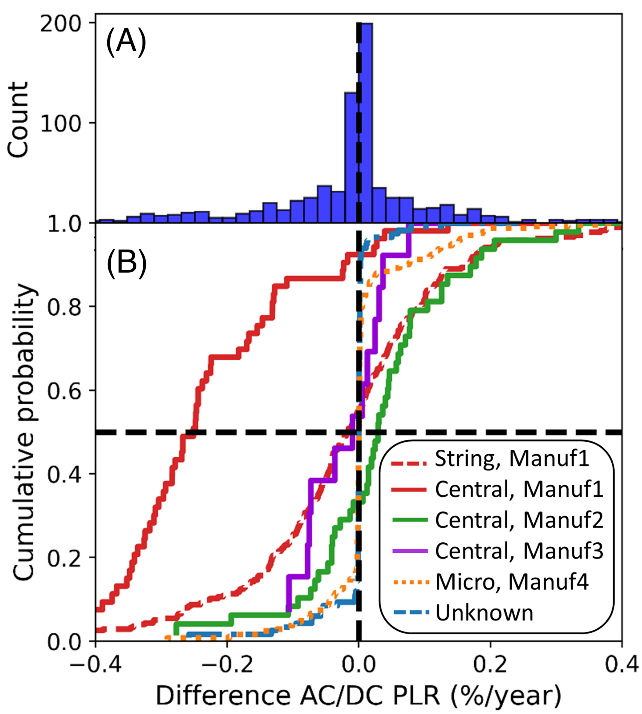

FIGURE 4 (A) Histogram of the difference between AC and DC performance loss rates. (B) Cumulative distribution function of the performance loss difference color coded by different technologies and inverter manufacturer

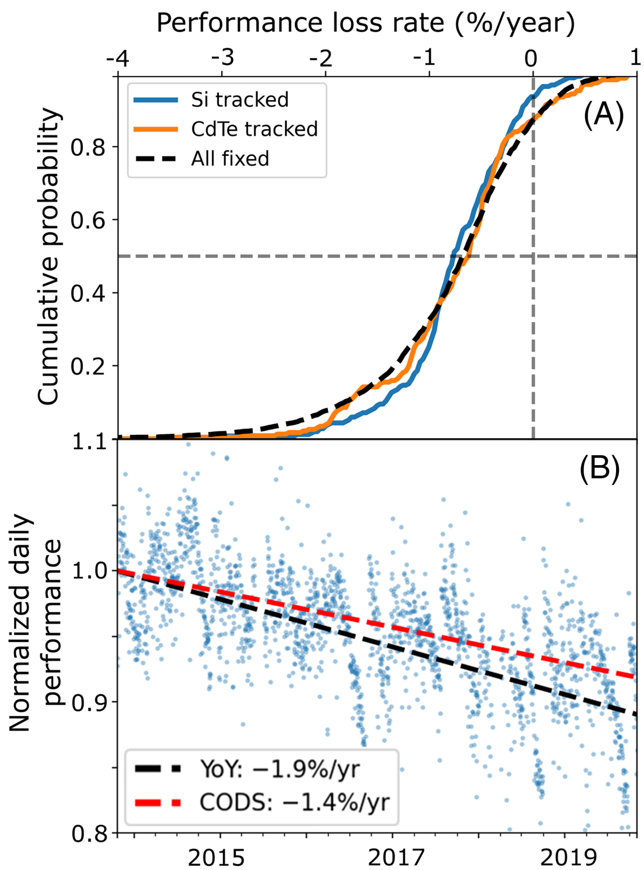

FIGURE 5 (A) Cumulative distribution of ground-mounted systems PLRs. All Si technologies on single-axis tracked systems (blue) and CdTe technologies on single-axis tracked systems (orange) are contrasted to all fixed-tilt systems (dashed black). The median and zero PLR are shown as guide to the eye as horizontal and vertical dashed gray lines, respectively. (B) Example of the normalized daily performance of a heavily soiled system that was excluded in the comparison along with two degradation trendlines

without details of the DC measurements accuracy, drift in the DC measurements cannot be ruled out as an alternative explanation. In addition, DC data are more likely instantaneous data compared with the more commonly time-averaged AC data that could contribute to some of the data noise that can be seen.

6 | MOUNTING CONFIGURATION

More large-scale ground-mounted systems installed today use single-axis trackers to increase energy yield. The dataset in this study allowed for the PLR comparison between fixed-tilt systems and single-axis tracking systems, as shown in Figure 5 and additional information provided in Table 3. The data are divided by module technology, separating CdTe module technology from Si technologies for tracked systems. Fixed-tilt systems have a great variety of sizes, whereas tracking systems tend to be larger. Unfortunately, the tracked systems could not be separated by technology that allowed statistically significant conclusions. The PLR for tracked versus fixed-tilt systems and CdTe versus Si systems does not show any statistical difference (p value > 0.49) although potential tracker failures have affected PLRs of tracked systems.[32] We should note that three tracked CdTe sites have been excluded from this comparison, all of which reside in a high-soiling area in California, and all of which exhibit signs of considerable seasonal soiling loss (Figure 5B). Yearly differences in soiling patterns are known to bias the year-on-year method of calculating degradation rates, especially when losses occur in the first or last year of the dataset. The combined degradation and soiling algorithm (CODS), which separates recoverable soiling loss from nonrecoverable PLRs, shows distinctly slower PLR when soiling is accounted for in heavily soiled systems.[33] Consequently, to avoid biasing the technology and mounting comparisons, we exclude these systems from the analysis. Because of computational requirements, the CODS algorithm could not be run on all systems but only on a few particularly high-soiling systems. Further investigation is required to enable appropriate treatment of significantly soiled PV systems.

7 | CLIMATE

Several studies have shown that climate is an important consideration for PV performance loss.[11,34–37] Because the details of the mounting configuration can also affect PLRs, we only investigated the impact of climate by selecting ground-mounted systems. Utilizing the PV climate zones introduced above, Figure 6 shows the PLR trend for conventional c-Si module (high-efficiency modules excluded) as a function of equivalent rack temperature zone. The equivalent rack temperature zone represents an Arrhenius-weighted equivalent temperature; the transition values between each zone are given in Table 4. A significant trend (p value < 0.001) of higher performance loss with hotter temperature climates can be discerned. The data are also color coded by the number of busbars used in the modules; however, no statistically significant trend with the busbars could be determined. As the industry transitions to higher number of busbars and multibusbars and deploys more systems in areas exposed to extreme climate, further investigation of PLRs with respect to number and type of busbars is warranted. Because of an uneven distribution of aluminum back surface field (Al-BSF) systems

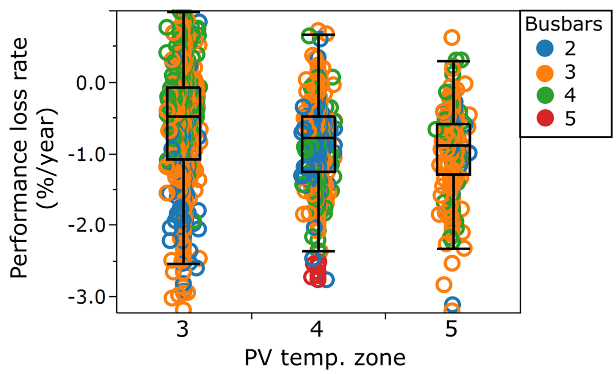

FIGURE 6 Boxplot of conventional Al-BSF systems as a function of PV temperature climate zone color coded by the number of busbars used in the modules. PV temperature zones are shown in Figure 1

TABLE 4 Performance loss rate statistics for different PV-specific temperature zones

PV temperature zone	Inverters	Sites	Median (%/year)	Mean (%/year)
T3	904	44	−0.48	−0.63
T4	407	43	−0.78	−0.91
T5	217	25	−0.88	−1.14

TABLE 3 Performance loss rate statistics for different mounting configurations

Mounting	Median (%/year)	Mean (%/year)	Inverters	Sites	Cumulative capacity (MW)
Fixed	−0.68	−0.79	3873	538	966
Tracked Si	−0.76	−0.76	252	37	124
Tracked CdTe	−0.61	−0.72	235	6	381

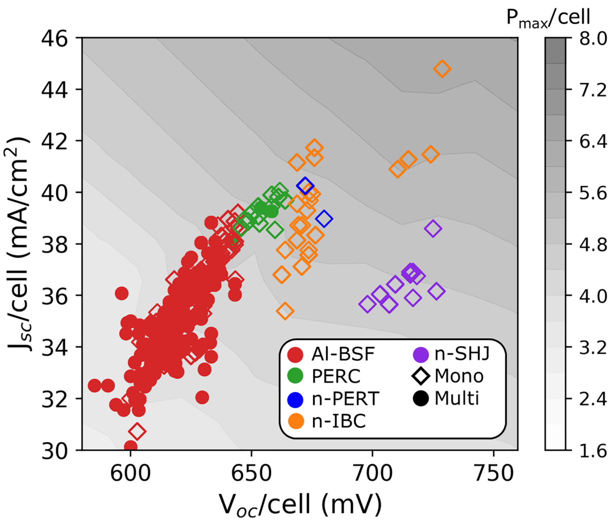

FIGURE 7 Contour plot of short-circuit current density, open circuit voltage, and maximum power per cell for all PV modules in the PV Fleet database normalized by the number of cells and cell size. Different cell technology is indicated by the color and crystallinity type indicated by symbols

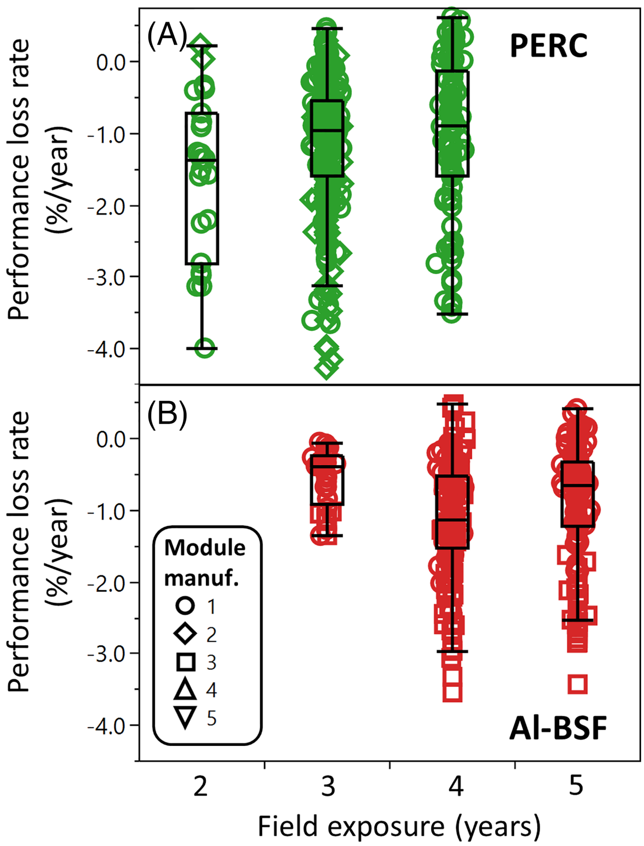

FIGURE 8 Performance loss rates for (A) PERC and (B) conventional Al-BSF containing systems in the first year of operation in similar climate in California

across zones, a trend with respect to humidity zones could not be determined with confidence.

8 | MODULE TECHNOLOGY

As the PV industry is undergoing a major technological shift, a more detailed investigation by technology is necessary. Conventional c-Si technology based on Al-BSF cell technology has been rapidly replaced by PERC technology. Although PERC cell technology was developed in the laboratory decades earlier, it became the mainstream Si technology only recently.[38] When the technology was first introduced as a commercial product, it was not always clear from the provided datasheet whether this particular cell technology was used in a given module. To aid in the identification of high-efficiency cell technology modules, a contour plot of the data sheet values for short current density (J_{sc}), open circuit voltage (V_{oc}), and maximum power (P_{max}) is depicted in Figure 7 for all the modules in the PV Fleet. Because the number of cells per module and the cell size has increased over time, the simple P_{max} output of a module is not necessarily indicative of the cell technology utilized. Therefore, in the contour plot Figure 7, the current–voltage (I–V) parameters from commercial module datasheets are normalized by the number and size of the cells. Cell technologies are indicated by different colors while symbols are used for mono-Si and multi-Si, respectively.

Several clusters of technologies can be identified; particularly, high-efficiency n-type technologies interdigitated back contact (IBC) and silicon heterojunction (SHJ) are easily identified through the higher V_{oc} per cell values. In contrast, Al-BSF technology—the dominant cell technology for many decades—is typically not explicitly specified on commercial datasheet and can be identified by the lower P_{max}, J_{sc}, and V_{oc} values. Indicated in red, it has developed along a diagonal of J_{sc} and V_{oc} but has reached its technological limits. PERC technology continues the evolution along the diagonal with greater gains apparent in voltage than before. If the cell technology is not known otherwise, the technology can be identified by its higher J_{sc}, V_{oc} values, and lower temperature coefficients compared with conventional technology. Because of a similarity in performance, a

TABLE 5 Performance loss rate statistics for PERC and Al-BSF in the first few years (CA temperature zones T3 and T4)

Technology	Field exposure (years)	Median PLR (%/year)	Mean PLR (%/year)	Inverters	Sites
PERC	2	−1.36	−1.64	23	6
PERC	3	−0.95	−1.12	353	53
PERC	4	−0.89	−0.89	103	18
Al-BSF	3	−0.39	−0.50	38	4
Al-BSF	4	−1.12	−1.01	215	19
Al-BSF	5	−0.64	−0.87	157	5

transition region exists between Al-BSF and PERC in which the graph may be inconclusive for some systems. However, we have verified most technologies in this range by private communication with former manufacturer employees. Another variant of the PERC family, the n-type passivated emitter and totally diffuse (PERT), is typically identified as such on datasheets and is characterized by higher V_{oc} and J_{sc} values compared with Al-BSF.

With the high-efficiency technologies identified with reasonable accuracy, we can start investigating the performance loss for the different technologies in more detail. In Figure 8, we examined PERC and Al-BSF-based ground-mounted fixed-tilt systems in the first few years of field exposure in the same temperature zones T3 and T4 in California, USA, with additional details provided in Table 5. It appears that the PERC systems show an improving degradation trend within the first few years of field exposure. However, the small number of data points, especially with 2 years of field exposure, is inconclusive. It is unclear if higher initial degradation may be caused by typical start-up issues or if a technology-inherent affect such as light and elevated temperature-induced degradation (LeTID) may be responsible.[39] In addition, most of the data in the first 2 years come from only one manufacturer. The Al-BSF on the other hand shows performance loss that does not show a clear trend with time.

Figure 9A depicts 3-year-old PERC systems from the two most prevalent manufacturers in our fleet with a consecutive comparison to other technologies. The solid green lines indicate the CDF analyzed in the normal way, that is, with an upper irradiance limit of 1200 W/m^2 intended to eliminate only extreme cloud brightening or erroneous values. The default lower irradiance limit is 200 W/m^2 and the two different manufacturers are indicated by different shades of green consistent with color usage in Figure 7. Manufacturer 2 shows a higher magnitude PLR at the median than Manufacturer 1 and also displays a much wider distribution indicated by the interquartile range given in Table 6. When the same systems are examined at low light only with an upper irradiance limit of 600 W/m^2, the PLR is significantly larger in magnitude for both manufacturers, as found by a paired t test (p value < 0.001). Shunts that typically manifest themselves at low light may or may not be responsible, or a different degradation mechanism entirely may be taking place.[40] It is also conceivable that this effect may be due to errors in the low-light model of performance used for energy normalization (PVWatts).

The median PLR for Al-BSF-based systems under normal (all-light) analysis conditions is similar to that of PERC systems under normal analysis. However, in contrast to the PERC systems, the low-light PLR for Al-BSF differs only by 0.09%/year from the normal analysis. The difference is almost an order of magnitude below that for the PERC manufacturers and is within the measurement uncertainty for individual PLR calculations. Interestingly, and possibly due to the large sample size, this small PLR difference is still statistically significant (p value $=$ 0.001). It should be noted that a broader geographic distribution for Al-BSF systems had to be used due to the lack of manufacturer variation in the Los Angeles, CA area. Al-BSF systems were all located in California in PV equivalent temperature zones 3 and 4, which should provide at least similar behavior.

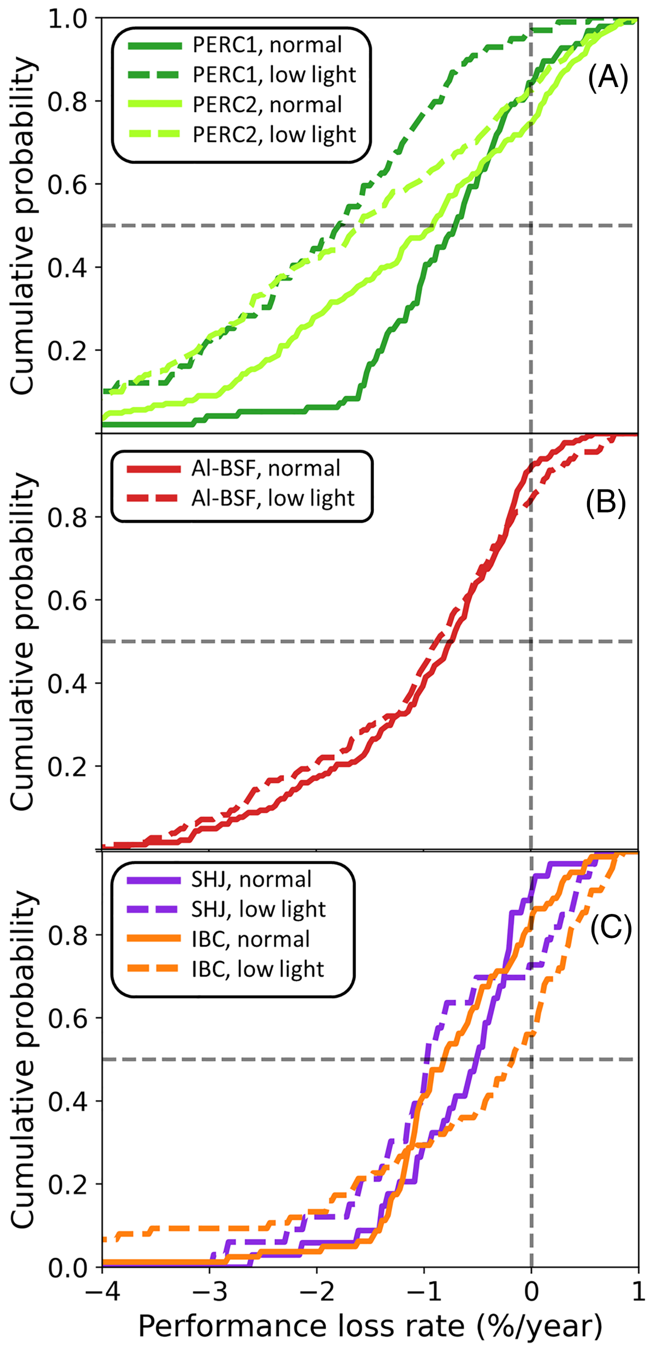

FIGURE 9 Cumulative distribution function of performance loss rates for (A) PERC containing systems from two different manufacturers, (B) Al-BSF, and (C) silicon heterojunction and interdigitated back contact systems. All systems are located in California in PV climate zones 3 and 4. All PERC systems were fixed tilt and ground mounted while all other technologies included a variation of mounting configurations. For normal (solid line) evaluation, the upper irradiance limit is set to a default value of 1200 and 600 W/m^2 for low-light assessment (dashed line)

The same California-wide sourcing applies to distributions of high-efficiency technologies SHJ and IBC in Figure 9C. SHJ shows behavior similar to PERC with a higher performance loss at low-light while IBC appears to show a less severe PLR at low light.

TABLE 6 Performance loss rate statistics for crystalline silicon systems using different cell technologies

Technology	Light level (W/m^2)	Median PLR (%/year)	Interquartile range (%/year)	Mean PLR light difference (low light–normal) (%/year)	Mean age (years)	Inverters	Sites
PERC1	1200	−0.69	1.06	−1.25	3	99	14
PERC1	600	−1.79	1.77		3	99	14
PERC2	1200	−0.91	2.18	−0.57	3	268	39
PERC2	600	−1.60	2.50		3	268	39
Al-BSF	1200	−0.74	1.28	−0.09	4.4	181	38
Al-BSF	600	−0.89	1.40		4.4	181	38
SHJ	1200	−0.51	0.86	−0.32	8	34	19
SHJ	600	−0.96	1.50		8	34	19
IBC	1200	−0.79	1.00	+0.52	4.5	85	19
IBC	600	−0.07	1.22		4.5	85	19

9 | CONCLUSION

The PV Fleet database, encompassing over 7 GW of mostly larger PV installations in the United States was examined for PLRs. The median system PLR was found to be −0.75%/year consistent with prior and other recent work. In general, inverter degradation did not contribute to system PLR, however certain manufacturers did demonstrate more rapid AC performance loss than DC performance loss. Tracked Si and CdTe systems showed no statistical difference versus fixed-tilt systems in the median range of −(0.6–0.8)%/year. Conventional Al-BSF technology showed a trend with higher magnitude PLR in higher temperature climates. Insufficient samples were available to identify any trend versus climate for other module technology. No trend was observed with the number of busbars used in Al-BSF modules; however, with the shift of the industry towards higher number and different topology busbars, that is a trend that should be investigated further in the future.

High-efficiency module types (PERC, SHJ, and IBC) showed PLR generally in the same range as conventional Al-BSF systems. However, low-light degradation trends are different, suggesting that unique performance loss mechanisms may be present in some of these module types. PERC systems showed markedly more rapid PLR at low light compared with normal evaluation conditions. SHJ also showed significantly higher magnitude PLR at low light, but IBC showed the opposite trend with reduced low-light PLR. This remains an open avenue of investigation.

Compared with prior module-level studies that have shown PLRs on the order of −0.5%/year, our results here are slightly more elevated. This may be caused by our system-level versus module-level measurements that may include additional losses such as series mismatch, soiling, and cabling which may account for the increase to −0.75%/year. On the other hand, our methodology using high-frequency data, automated data quality screening and filtering for availability, clipping, and some seasonal effects corrects for factors that a coarse analysis based only on annual energy generation might neglect. With our results to date, we can report good health of the US PV fleet, along with some minor variations due to climate, racking configuration, and some interesting trends in newer module technologies.

ACKNOWLEDGEMENTS

We would like to thank our corporate partners who provided the PV system data used to perform the analyses in this document. We would also like to thank the NREL PV reliability group, Martin Green, and Katherine Jordan. This work was authored in part by Alliance for Sustainable Energy, LLC, the manager and operator of the National Renewable Energy Laboratory for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding is provided by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under Solar Energy Technologies Office (SETO) Agreement Number 30295. The views expressed in the article do not necessarily represent the views of the DOE or the US Government. The US Government retains and the publisher, by accepting the article for publication, acknowledges that the US Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for US Government purposes.

ORCID

Dirk C. Jordan https://orcid.org/0000-0002-2183-7489
Kevin Anderson https://orcid.org/0000-0002-1166-7957
Kirsten Perry https://orcid.org/0000-0002-8095-7472
Matthew Muller https://orcid.org/0000-0002-3835-4096
Michael Deceglie https://orcid.org/0000-0001-7063-9676
Robert White https://orcid.org/0000-0002-5208-4061
Chris Deline https://orcid.org/0000-0002-9867-8930

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How to cite this article: Jordan DC, Anderson K, Perry K, et al. Photovoltaic fleet degradation insights. *Prog Photovolt Res Appl*. 2022;30(10):1166-1175. doi:10.1002/pip.3566