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Evaluation of Component Reliability in Photovoltaic Systems using Field Failure Statistics

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ABSTRACT

Ongoing operations and maintenance (O&M) are needed to ensure photovoltaic (PV) systems continue to operate and meet production targets over the lifecycle of the system. Although average costs to operate and maintain PV systems have been decreasing over time, reported costs can vary significantly at the plant level. Estimating O&M costs accurately is important for informing financial planning and tracking activities, and subsequently lowering the levelized cost of electricity (LCOE) of PV systems. This report describes a methodology for improving O&M planning estimates by using empirically-derived failure statistics to capture component reliability in the field. The report also summarizes failure patterns observed for specific PV components and local environmental conditions observed in Sandia's PV Reliability, Operations & Maintenance (PVROM) database, a collection of field records across 800+ systems in the U.S. Where system-specific or fleet-specific data are lacking, PVROM-derived failure distribution values can be used to inform cost modeling and other reliability analyses to evaluate opportunities for performance improvements.

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ACRONYMS AND DEFINITIONS

Abbreviation	Definition
AC	Alternating current
AIC	Akaike information criterion
BIC	Bayesian information criterion
CDF	Cumulative distribution functions
DC	Direct current
GW	gigawatt
IGBT	Insulated Gate Bipolar Transistors
kW	kilowatt
LCOE	Levelized cost of electricity
NREL	National Renewable Energy Laboratory
O&M	Operations and maintenance
P-P	Probability-probability
PV	Photovoltaic
PVROM	Photovoltaic Reliability Operations and Maintenance
Q-Q	Quantile-quantile
SNL	Sandia National Laboratories
TTF	Time to failure
TTR	Time to Repair

1. INTRODUCTION

Ongoing operations and maintenance (O&M) are needed to ensure photovoltaic (PV) systems continue to operate and meet production targets over the lifecycle of the project. Although average costs to operate and maintain PV systems have been decreasing over time, reported costs can vary significantly at the plant level from $12/kilowatt (kW)/yr. to $30/kW/yr. (Bolinger et al., 2017). Estimating O&M costs accurately is important for informing financial planning and tracking activities, and subsequently lowering the levelized cost of electricity (LCOE) of PV systems.

O&M costs of a PV system vary as a function of specifications (e.g., inverter type, tracking system), component reliability (time to failure), environmental conditions, and administrative costs (e.g., property taxes, warranties) (Walker, 2017). Subsequently, the input requirements for generating detailed O&M cost estimates can be significant. While some of the cost model parameters can be informed by contractual agreements (especially administrative costs) or manufacturer specifications, empirically-derived failure statistics are also required to capture component reliability in the field (Hacke et al., 2018). In addition to informing cost models, field failure statistics can also be used to evaluate opportunities for performance improvements through reliability simulations (Miller et al., 2012).

Due to the diverse practices used for tracking O&M activities across the PV industry, the collection and processing of field data can be challenging. To address the need for improved analysis based on field data, this report describes an updated methodology for deriving component-level failure statistics with a focus on component reliability. Finally, the report summarizes failure rates observed in the PV Reliability, Operations & Maintenance (PVROM) database, a collection of field records across 800+ systems in the U.S. Where system-specific or fleet-specific data are lacking, the PVROM-derived values can be used to inform cost model estimates and other reliability analyses.

NOTE: Development of failure rates using field observations is critical for improving the accuracy of PV O&M cost models.

2. HOW TO: FAILURE RATES ANALYSIS

The analysis of failure rates consists of three primary steps: 1) collection of relevant data, 2) processing of data, and 3) implementation of statistical methods (Figure 2-1). The collection of relevant data requires answers to two key questions: 1) what is the failure of interest? and 2) what field data is available regarding the failure of interest? After the relevant data is collected, processing is required to generate the required features for statistical analysis. This includes tabulation of time to failure (TTF) numbers and verification of the processed data quality. Once the data is processed, statistical analysis is conducted to tabulate the failure distribution parameters. Depending on the analysis objectives and data availability, failure rates can be analyzed using either non-parametric or parametric methods.

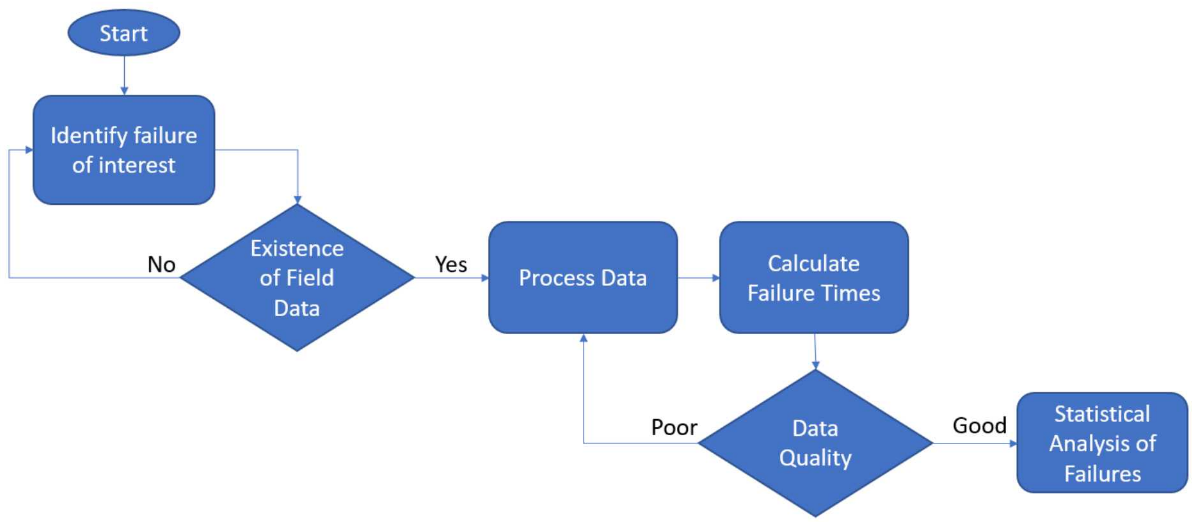

Figure 2-1. Summary of Decision Flow Associated with Failure Rates Analysis

2.1. Relevant Data Collection

Collection of relevant data depends on the failure of interest. The most common definition of failure refers to equipment not performing required actions (Jordan et al., 2017). However, failures can be defined in different ways for different assets. In the context of PV systems, failures can refer to issues at the system-level or for a specific asset and can refer to equipment underperforming or not performing at all. The O&M cost model (developed in partnership by the National Renewable Energy Laboratory (NREL), Sandia National Laboratories (SNL), etc.) identifies a number of failure activities prevalent in PV systems (Walker, 2017). Examples of PV failures include inverters and trackers malfunctioning, fuse failure, and degradation due to environmental conditions.

The resolution of available data often guides the level of detail achievable with the failure analysis. For example, if field records only state that "inverters are offline" or that the "site is offline", then evaluating patterns for specific failures (e.g., due to ground fault or software issue) is not feasible.

Common datasets used for failure analysis are based on maintenance records that document unplanned activities in response to equipment failures. Maintenance records are captured in a variety of formats, ranging from hand-written notes to formal, digitized entries in a computerized maintenance management system. The details captured in the maintenance records can also vary, with some entities capturing nuances of when an event started and ended to some also capturing when the associated field work and financial paperwork were completed. For failure analysis, the primary items of interest from maintenance (or other incident) records include:

- Date/time of failure occurrence,
- Consistent and clear description of the problem (including details about affected component and corrective actions taken to address failure), and
- Date/time of resolution of the failure.

Some records capture details about the specific component failure and corrective actions in a narrative format whereas other capture them in distinct and consistent categories. For the former, an interpretation of the records is required to identify those relevant to the failure of interest. This manual interpretation introduces subjectivity in the analysis process. If the records are digitized and consistent, searching for key terms or (where sufficient data is available) advanced data analytic techniques including machine learning can be used to identify records of interest (Gunda, 2020). If there are no records related to a particular failure of interest, then another failure should be selected for analysis (Figure 2-1).

NOTE: Contextual details regarding commissioning details, climate exposure, and warranty details of the system and/or specific assets can influence the interpretation of the maintenance records.

2.2. Data Processing

After the relevant failure records are collected, processing is required so that the data can be used for statistical analysis. Specifically, while the maintenance records may capture the date of failure, they do not capture details regarding the time to failure (TTF). Thus, these values need to be calculated. TTFs are calculated by evaluating the amount of time that transpired between when the equipment initial operation and the failure occurrence. Moreover, depending on the resolution of the available data, the analysis may be restricted to evaluations of only the initial failure for a given system, if details about which specific piece of equipment experienced failures are lacking.

Some equipment may not have failure data at the time of analysis, either because a system went offline prior to experiencing that failure or because observations ended at the site before system experienced the failure. This data is considered to be censored and should be included in the analysis to capture patterns associated with lack of failures. For equipment with no observed failures, records are created that describe the length of period observed (i.e., "right" censoring or censoring occurring at the end of the observed period). Inclusion of the right-censored data represents the incomplete knowledge associated with the dataset being analyzed. An example of processed data is shown in Table 2-1. The "status" column captures details about whether a failure was observed (1) or not observed during the period observed (0). Similar datasets can also be constructed for time to repair (TTR) analysis.

Finally, a data quality check is required to ensure that the processed data is suitable for statistical analysis. At a minimum, the data should be evaluated for inconsistencies, such as dates of failure occurring before dates of failure resolution (i.e., TTF < 0). Other checks can be implemented depending on the data resolution and intended use (e.g., time that field work is completed occurs before the time that the ticket is closed).

Table 2-1. Example of Processed Data.

Record	TTF (days)	Status
1	82	0
2	49	1
3	35	0
4	100	1
5	90	1
6	63	1

For records with status = 1, the time to failure (TTF) captures the amount of time between equipment's initial operation and observed failure. For records with status = 0 (i.e., no failure), the TTF captures the amount of time observed since the equipment began operating.

NOTE: Contextual details about the maintenance records (e.g., age of systems analyzed and how information is collected) can greatly influence the quality of the initial data processed.

2.3. Statistical Analyses

After data processing is completed, the resulting data is used to create failure statistics. Below two approaches are described for generating failure statistics: non-parametric and parametric. The non-parametric approach does not make any assumption about the underlying distribution of the data and is most effective for statistical analysis of small datasets. In contrast, the parametric approach is focused on fitting the data to a specific distribution; this approach requires meeting assumptions of the underlying data's distribution. If these assumptions can be met, parametric approaches have higher statistical power than non-parametric approaches (Zimmerman and Zumbo, 1993). Multiple software tools can be used to calculate failure statistics for a given dataset (Klise et al., 2018). Example code using the open source software R for both the non-parametric and parametric approaches is provided below.

2.3.1. Non-Parametric Approach: Kaplan-Meier estimator

The Kaplan-Meier estimator is a non-parametric approach for evaluating survival over time that is able to accommodate censored data in its calculation. The Kaplan-Meier estimator estimates the probability that a system has not experienced a failure by a given point in time. In other words, the Kaplan-Meier estimator gives a point estimate of systems' reliability for a given failure at a specific point in time. The estimator can be plotted over time to illustrate how many systems are expected to experience their first failure as time progresses. This estimator represents a conditional probability of failure. That is, if a system has not yet experienced a failure, what is the probability that it will fail by time t? The Kaplan-Meier estimator of survival is given by

$$\hat{S}(t) = \prod_{k:t_{(k)} \leq t} \frac{n_k - d_k}{n_k} = 1 - \hat{P}(t)$$

where

$t_{(k)}$: time to k^{th} failure;

n_k= number of systems at risk at the beginning of time period $t_{(k)}$, that is, the number of systems that have not yet experienced a failure right before $t_{(k)}$;

d_k= number of systems that fail during period $t_{(k)}$;

$\hat{P}(t)$ = the estimated probability of failing during period $t_{(k)}$.

Confidence intervals can be computed for the Kaplan-Meier point estimate. To do so one must first estimate the standard deviation of the estimator. The variance of $\hat{S}(t)$ is given by

$$\widehat{Var}\left[S\left(t_{(k)}\right)\right] = \sigma^2\left(t_{(k)}\right) = [1 - \hat{P}\left(t_{(k)}\right)]^2 \sum_{l \le k} \frac{d_l}{n_l(n_l - d_l)}$$

which allows for calculation of a 95% confidence interval on $\hat{S}(t)$ as

$$S_{95\%}\left(t_{(k)}\right) = \hat{S}(t_k) \pm 1.96\sigma(t_k)$$

Since survival is a rate, it ranges from zero to one; hence, so its confidence interval should as well. As a result, the upper bound of the confidence interval is calculated as

$$\min\left\{1, \hat{S}(t_k) + 1.96\sigma(t_k)\right\}$$

And the lower bound is given by

$$\max\left\{0, \hat{S} - 1.96\sigma(t_k)\}\right\}$$

An implementation of the Kaplan-Meier estimator using the "survival" package in R (Therneau, 2020) is shown below. In this example, "df" represents the processed data containing details about the TTF (days) and associated status:

```
library(survival)
surv_object <- Surv(time=df$TTF_days, event=df$status)
kmfit <- survfit(surv_object ~ 1, data=df)
summary(kmfit)
```

2.3.2. Parametric Approach: Weibull Distribution

While a non-parametric approach allows for more flexibility, a parametric approach is often necessary for reliability analyses. Visualizations and goodness-of-fit tests can be used to identify the distribution that best represents the data. Example visualizations include quantile-quantile (Q-Q) plots and probability-probability (P-P) plots, which compare the theoretical cumulative distribution functions (CDFs) of the distribution model to the empirical CDF. Closer alignment between the empirical CDF and a theoretical CDF (i.e., the closer the points are to the line y=x) indicates better fit of the data to the distribution. Users should use Q-Q plots to inspect the tails and P-P plots to inspect the center of the distributions. If a visual inspection of the plots does not reveal a clear choice among the candidate theoretical distributions, a more rigorous quantitative approach can be employed to make the distinction. Metrics such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and log-likelihood, can provide a quantitative basis for goodness-of-fit evaluations. Smaller values of AIC and BIC and larger values of log-likelihood indicate better statistical model fit.

The Weibull distribution is commonly used in reliability analyses due to its flexibility (Nelson, 1985). For example, a Weibull with a shape factor (beta) of 1 is the same as an exponential distribution with a constant failure rate. More details are provided below about this distribution and its implementation. Additional information about fitting other distributions to failure data can be found in Klise et al., (2018) and Delignette-Muller and Dutang (2014).

The hazard function, which represents the instantaneous rate of occurrence for the failure, for the Weibull distribution is defined as (Madigan, 2004):

$$h(t) = \beta\alpha t^{\alpha-1}$$

The associated survival function for the Weibull distribution is then,

$$\hat{S}(t) = e^{-\beta t^{\alpha}}$$

where

t: time to k^{th} failure;

α: shape parameter; and

β: scale parameter.

The shape parameter represents the pattern of risk over time. If α =1, then the probability failure is constant over time; values greater than 1 indicate an increase in failure probability over time and values less than 1 indicate a decrease in failure probability over time. For a given shape value, increasing the scale stretches the distribution to the right (i.e., increases the mean time to failure) and vice versa.

An implementation of the Weibull estimator using the "survival" package in R is shown below. As noted above, "df" represents the processed data containing details about the TTF (days) and associated status:

```
library(survival)
surv_object <- Surv(time=df$TTF_days, event=df$status)
weibfit <-survreg(surv_object ~ 1,data = df, dist = "weibull")
summary(weibfit)
```

Exponential, Gaussian, logistic, lognormal, log logistic, and user-defined distribution parameters can also be calculated using the "survival" package.

NOTE: Larger datasets increase the robustness of the derived statistical parameters. Dataset size can be augmented, either by using longer periods of observation or by increasing the number of assets and systems considered in the analysis.

3. FAILURE PATTERNS FROM PVROM

Sandia's PVROM database contains a collection of 50,000+ maintenance records from 800+ systems across the country (Figure 3-1). The systems represent a total capacity of 5.1 gigawatts (GW) of direct current (DC) and 3.9 GW of alternating current (AC). Information about some of the failures referenced in the PV O&M cost model (Walker, 2017), including associated patterns extracted from the PVROM database are presented in this section.

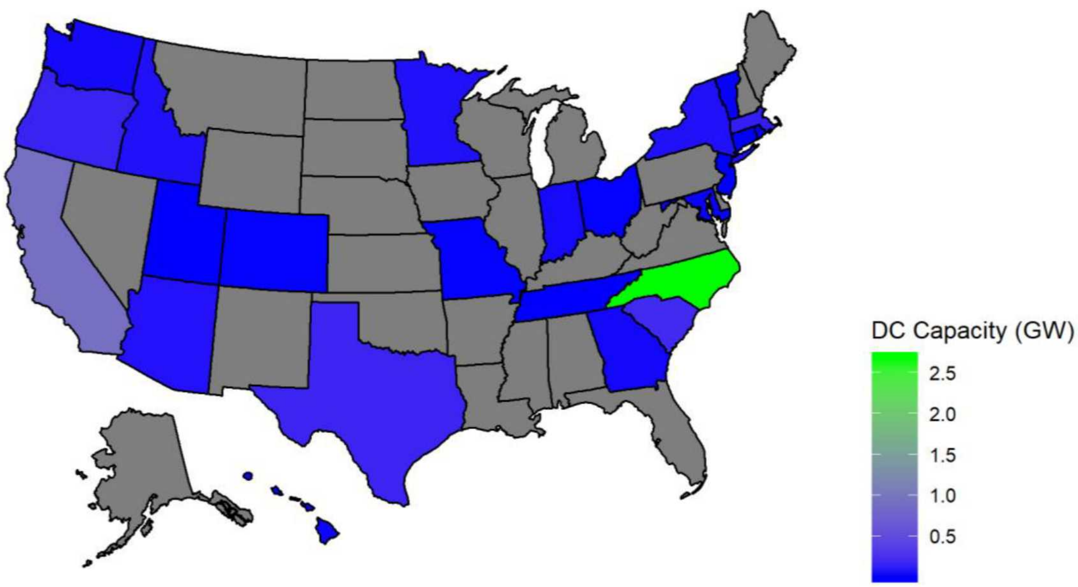

Figure 3-1. Geographic coverage of Sandia's PVROM Database, as of August 2020.

Data observed in PVROM have the following properties: 1) dates when operations began are known and vary by system, 2) failure dates and censor dates are random, 3) censoring is "right" (as opposed to "left") because it occurred toward the end of the study period (as opposed to the beginning). Variations in the actual operation dates are addressed by the calculations of TTF, which captures the time between operation dates of the equipment and the failure event. TTR analysis is not conducted due to poor quality and insufficient details in the maintenance data.

3.1. Component Failures

While the records contain details about the general PV equipment involved (e.g., inverter, tracker, and module), there are insufficient details regarding the specific piece of equipment associated with each failure event. Thus, the failure analysis is limited to the occurrence of first failure for a system.

A summary of the mean time to failure and associated Weibull parameters for different activities are provided in Table 3-1. Additional details about these failures are provided in the following subsections.

Table 3-1. Summary of Failure Patterns observed in PVROM.

Activity Description	Mean Time to Failure (years)	Weibull Parameters	
		Shape (α)	Scale (β)
Insulated gate bipolar transistors matrix in inverter*	1.9	0.81	6.01
Inverter fan motor	2.2	1.04	11.03
Inverter reboot to clear unknown error	1.6	0.86	6.24
Broken modules	2.3	1.29	10.95
Damaged racking	1.5	0.83	8.36
Hydraulic cylinder	1.0	1.14	17.16
Tracker motor controller	1.1	1.10	1.52
Tracker bearing(s)	1.7	1.28	2.18

*Note: Analysis was conducted at an annual scale. Shape values greater than 1 indicate an increasing likelihood of failure over time. *Source: Gunda (2020)*

3.1.1. Inverters

Most of the entries in PVROM are related to inverters, which are arguably the most important balance of system component in a PV system for energy production (Hacke et al., 2018). Inverters, which convert DC to AC, provide a bridge between solar panels and electricity generated for the grid or home (Formica et al., 2017). When an inverter fails, the system produces little or no power. Thus, recognizing faults in the inverters is very important for increasing the reliability and efficiency of power electronic converters since individual faults cause reduced efficiency and eventually lead to complete system failure (Singh et al., 2015).

A notable inverter-related failure in the PVROM database relates to insulated gate bipolar transistors (IGBTs). Since IGBTs modulate and filter current at very high speeds based on voltage, their failure impacts overall inverter functionality (Doyle et al., 2019). Approximately 10% of the systems in the PVROM database mention failures in IGBTs, occurring on average at 1.9 years after system operations commence.

Another common failure in inverters occurs due to overheating. Since inverters are sensitive to temperature variations, regulating the temperature (using cooling systems) prevents premature aging, leading to improved performance. A typical air-cooled system consists of cooling fans, freeze plugs, thermostat, radiator, heater core, pressure cap, overflow tank and hoses (Grubišić-Cabo et al., 2016). A quarter of the systems in the PVROM database discuss cooling fan motor-related issues, with issues occurring, on average, 2.2 years after initial operations.

When the underlying cause of an inverter failure is not clear, technicians and operators often resort to resetting the system, as a first response, to bring the inverter to normal operational state (Lucero, 2018). These activities can either be done manually or remotely. Over 40% of the systems within PVROM discuss resetting of inverters as a response to an unspecified failure. This activity occurs on average at 1.6 years after initial operations, occurring more frequently than IGBT or cooling system-related issues. Additional details about inverter failures can be found in Gunda (2020).

3.1.2. Modules

PV module-related failures include cracked glass, cracked back sheets, and damages to the racking structures.

At least 1/5 of the systems in PVROM discuss broken modules arising from cracked glass. Cracked glass can be caused by many different factors (including ice, hail, and debris) and is usually accompanied by discoloration (Strauch et al., 2010). Cracked glass issues can also emerge near burn spots (Strauch et al., 2010). Some cracks can start small and due to heat and weather, grow and create system-level problems (Solar Engineering Group, 2016). According to the PVROM database, broken modules occurred on average 2.3 years after operations commenced.

Although backsheets are exposed to the sun less than other parts of the system, they still experience stress due to snow, wind, dust, and pressure. These stresses can lead to cracks in the back sheets, eventually leading to faults and forced system outages. Humid environments are especially prone to cracking and delamination in module backsheets (Lin et al., 2015). Only one system in the PVROM database discussed backsheet issues so distribution parameters were not derived for this failure.

Unlike backsheet issues, damages to the rack systems are more frequently captured within PVROM. Over 1/3 of the systems discuss issues related to either sinking, leaning, or otherwise damaged racks. Moreover, rack-related issues are discovered throughout the year, with a local maximum occurring in March (Figure 3-2). The average TTF for rack-related failures is 1.5 years after operations began.

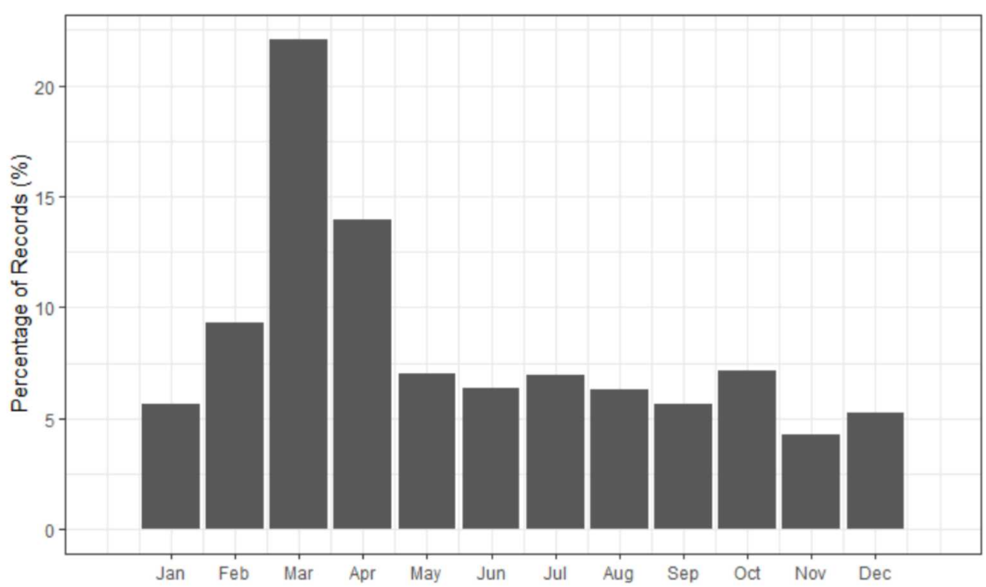

Figure 3-2. Occurrence of Rack-Related Damage Tickets

3.1.3. Trackers

Trackers improve production by orienting solar panels toward the sun such that the angle of incidence is minimized. The rotation of trackers (either on a single-axis or a dual-axis) is enabled by motors and associated controllers. Motors vary in efficiency, lifespans, and maintenance rates. Motors can be affected by strong winds (e.g., during hurricanes), leading to solar tracker failures (Burgess et al., 2018). Controller algorithms are designed so that the tracker system follows the sun intelligently, by using algorithms to position the solar cell and increase the sunlight falling on the array. Failures in the controller algorithm lead to system performance degradation due to inability to receive the sun's light at the desired/optimal angle and time duration (Rumbayan and Putro, 2017). In the PVROM database, 76% of the systems (with non-fixed systems) discuss issues related to the tracker motor or the tracker controller unit; these issues occur on average, 1.1 years after operations began.

Under normal operating conditions, most bearings outlive the equipment in which they are installed. Only a few bearings fail during equipment operation. When a problem with bearings occurs, troubleshooting can provide additional insights. Improper mounting techniques or inappropriate screw sizing, for example, can easily damage bearings and cause premature failure or degraded efficiency (Burgess and Goodman, 2018). Bolt self-loosening of modules - commonly caused by vibration - can also degrade the module's performance and efficiency (Burgess and Goodman, 2018). If bearings have been damaged, underlying root cause should be performed to understand and reduce risks. Within PVROM, over 77% of the systems (with non-fixed mounts) discuss fastener-related issues related to bearings, nuts, and bolts. These failures occurred, on average, 1.7 years after systems begin operating.

3.2. Local Environmental Conditions

The O&M of PV systems is also greatly influenced by local environmental conditions, such as vegetation, snow, dust, and pollen. Below, issues caused by each of these conditions is described in greater detail, including a discussion of the times of the year at which these activities generally occur in the PVROM database.

3.2.1. Vegetation

Vegetation management is required to reduce shading issues, damages from fallen branches, and control site erosion. Since the amount of sunlight received by the PV systems determines their power output, shadowing of the solar cells decreases their power output, with actual decreases in energy production often more significant than expected (Brown, 2016). Vegetation and the associated effects can vary greatly, based on the geographic region and type of climate. For example, vegetation management in hot and dry climates is required to reduce likelihood of fires (Beatty et al., 2017). Entries within PVROM discuss vegetation management both in the context of preventative maintenance (typically occurring in two phases, between Apr-Jun and Sep-Oct) as well as corrective maintenance (mostly outside of the winter months) (Figure 3-3). Corrective maintenance address issues related to shading, wire management, ground faults, or damaged modules as a result of poor vegetation management. A few records in the PVROM database also discuss triggering of trackers into snow stow mode from vegetation being high even where there is no snow present.

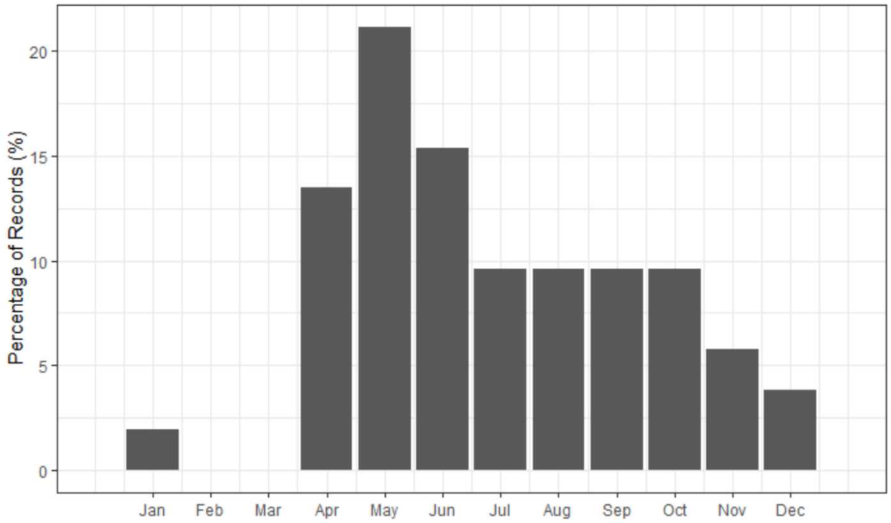

Figure 3-3. Occurrence of Vegetation-Related Tickets

3.2.2. *Snow*

Although cooler temperatures can improve the efficiency of solar production, snow on modules causes degradation in energy production, especially in low tilt systems (Gwamuri at al., 2015; Gautam, 2020). Furthermore, the weight of the snow can put stress and damage the structural support of the racks due to the non-uniform localized stresses at the mounting points; these stresses can also create microcracks in the modules (Gay, 2017). Within the PVROM database, snow-related issues resulted in forced and unplanned outages at both the inverter- and plant-levels. In some cases, trackers set to stow mode became stuck in this position. Snow can also affect the surrounding areas, which in turn affect the system. For example, one of the events in PVROM discuss a local grid outage resulting from a vehicle running into a pole. These issues were most commonly observed in the late fall, winter, and spring months across the New England, mid-Atlantic, and upper Midwest regions parts of the country (Figure 3-4).

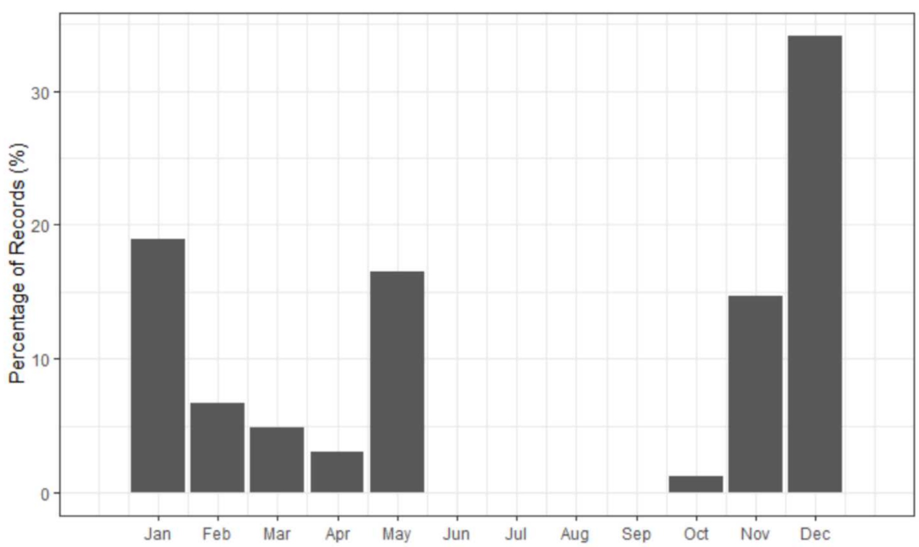

Figure 3-4. Occurrence of Snow-Related Tickets

3.2.3. Soiling

Airborne particles can significantly reduce output, degrading the system's performance (Hussain et al., 2017). Soiling of solar panels can emerge from a number of sources, including bird poop, pollen, dust, and dirt. The local climate (e.g., dry conditions or spring season) and land use (e.g., farming-related activities) can influence the amount of soiling (NREL, 2017). Soiling stations are used to monitor the amount of soiling on a system and also used to adjust estimates of expected energy values. The majority of the soiling-related issues in the PVROM database are reported during the month of June (Figure 3-5). Most of the tickets during the months of February and September reference soiling station-related activities.

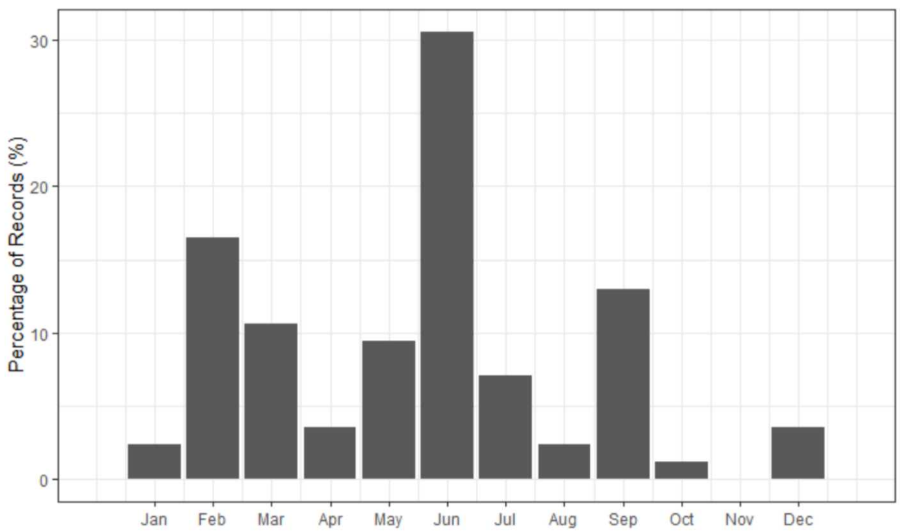

Figure 3-5. Occurrence of Soiling-Related Tickets

4. CONCLUSION

Effective O&M is crucial to ensure PV systems continue to meet production targets over their lifecycle. Due to diverse environmental conditions and O&M practices at PV systems, the associated O&M costs for PV systems can vary greatly. While the overall O&M costs for PV systems have been decreasing, significant opportunities exist for reducing the variabilities in O&M costs between systems. This report describes a statistical approach for deriving failure distribution parameters that can be used to inform O&M planning and reduce associated costs. This methodology is implemented using field data collected from 800+ U.S. systems, stored within Sandia's PVROM database.

A few notes should be made regarding the analysis of PVROM. First and foremost, the values presented in Table 3-1 represent aggregate patterns across multiple geographies (with varied climates) and across PV system manufacturers and model types. Although characterizing failure patterns is informative, ultimately, understanding the cause of each failure is needed to help reduce and mitigate risks. Unfortunately, root cause analysis is generally not conducted for events captured in the PVROM database; hence, the root cause for failures is not known.

In the course of analyzing PVROM failure data, significant challenges associated with data availability, consistency, and completeness were encountered. Standardization of failure data collection and capture can greatly reduce the processing time and improve the consistency and subsequently, the accuracy of associated analyses. Improving the resolution of collected data (to specific pieces of equipment using unique identifiers) will also improve the component-level failure rate analysis and lead to more refined values. For example, capturing the identifiers of components will enable evaluations of recurring failure patterns, which can help inform subsequent root cause and failure modes and effects analyses.

Finally, the age of the plants within PVROM is generally low - between 2-6 years, reflecting the general pattern of young plants within the industry (Jordan et al., 2020). Thus, continued data collection and analysis are required to improve our understanding of PV component reliability as plants age.

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