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PV System Component Fault and Failure Compilation and Analysis

Geoffrey T. Klise
Olga Lavrova
Renee Gooding

Prepared by
Sandia National Laboratories
Albuquerque, New Mexico 87185 and Livermore, California 94550

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Geoffrey T. Klise
Energy and Water Systems Integration
Sandia National Laboratories
P. O. Box 5800
Albuquerque, New Mexico 87185-MS1137

Olga Lavrova
Photovoltaic and Distributed Systems Integration
P. O. Box 5800
Albuquerque, New Mexico 87185-MS1033

Renee Gooding
Special Analytic Initiatives
P. O. Box 5800
Albuquerque, New Mexico 87185-MS1324

Abstract

This report describes data collection and analysis of solar photovoltaic (PV) equipment events, which consist of faults and failures that occur during the normal operation of a distributed PV system or PV power plant. We present summary statistics from locations where maintenance data is being collected at various intervals, as well as reliability statistics gathered from that data, consisting of fault/failure distributions and repair distributions for a wide range of PV equipment types.

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1. INTRODUCTION

This paper provides a summary of photovoltaic (PV) component maintenance data collected and analyzed by Sandia National Laboratories (SNL) in support of the PV Operations and Maintenance project led by the National Renewable Energy Laboratory (NREL). Some of this data collection was initiated in 2003 by SNL under a separate project with more recent data collected during the FY 2016-2018 period of project performance.

The purpose of this data collection and analysis is to provide statistical insight into how components fault and fail in a PV system or power plant. This information can be used to inform software such as the PV O&M Cost Model (NREL, 2016), developed by NREL, the SunSpec Alliance (SunSpec) and SNL. Many of the failure distributions presented here can be used with the SNL PV-Reliability Performance Model (Klise et al., 2017) which is now a feature within NRELs System Advisor Model (SAM) for simulating how faults and failures can impact lifetime energy performance and cost.

As data collection efforts continue, the appendices in this report will be updated along with discussion on insights gained from additional years of data collection, and addition of new sites to the database.

2. DATA COLLECTION SUMMARY

2.1. Portfolio Description

The main data collection effort started in 2007 when SNL had access to maintenance records from the Springerville power plant in Arizona (Collins et al., 2009; Collins et al., 2010; Klise et al., 2014). Additional efforts were made with an O&M provider in Arizona starting in 2011, with 1.75 MW of PV distributed generation (DG). Two additional data partners as described in Klise et al., 2014 with 0.45 MW of DG and 34 MW of utility scale generation started delivering data in 2014, however the data was not complete as the data partners discontinued participation. Two additional data partners were brought in during 2015 and include owner-operators with large portfolios of DG and utility-scale installations that span multiple U.S. states. Since the start of the current phase of the project, with NREL as a partner in supporting the development of additional reliability distributions, the database increased 24% with the addition of 61 more PV systems from what is labeled as Portfolio D (Figure 1). The reliability data presented here will be from four portfolios as presented in Table 1.

Table 1. Portfolio Summary

Portfolio	Commissioning year	Data collection range	Number of PV systems	MW_{DC}	% of DG systems	% of utility scale systems
A	2003	2003-2008	1	3.5	0	100
B	2008-2009	2012-2014	2	1.75	100	0
C	2008-2016	2015-2016	180	578	3.4	96
D	2010-2017	2013-2017	61	25.6	100	0

2.2. Component Fault/Failure Summaries

For the portfolio of maintenance data, only 109 out of the 189 PV systems have maintenance data recorded against specific components. This represents around 510 MW_{DC} out of a total 780 MW_{DC}. The data collection range is limited for each portfolio as shown in Table 1. Some of the portfolios only show events at the inverter level, with discussion on what may have caused an inverter to trip based on an issue with a module string, or combiner, for example.

Table 2 presents a summary of some of the major components in each portfolio. Other components, such as disconnects or strings, for example, are tracked for faults and failures, though counts of those components are not available.

Table 2. Component Summary for Each Portfolio

Portfolio	Unique module manufacturers	Unique module models	Total number of modules	Unique inverter manufacturers	Unique inverter models	Total number of inverters
A	1	1	11,700	1	1	26
B	1	2	7,830	1	2	7
C	19	51	2,636,626	10	47	970
D	11	25	83,891	8	29	129
Total	24[i]	58[i]	2,740,047	12[i]	50[i]	1132

i – Total unique manufacturers and models. This value is not the sum of A through D as some of the same component manufacturers are found between Portfolios.

Figure 1 presents a high level summary of events across all portfolios, sorted by the greatest number of faults and failures to the lowest. At the inverter level, this can include faults on the DC side that caused the inverter to trip.

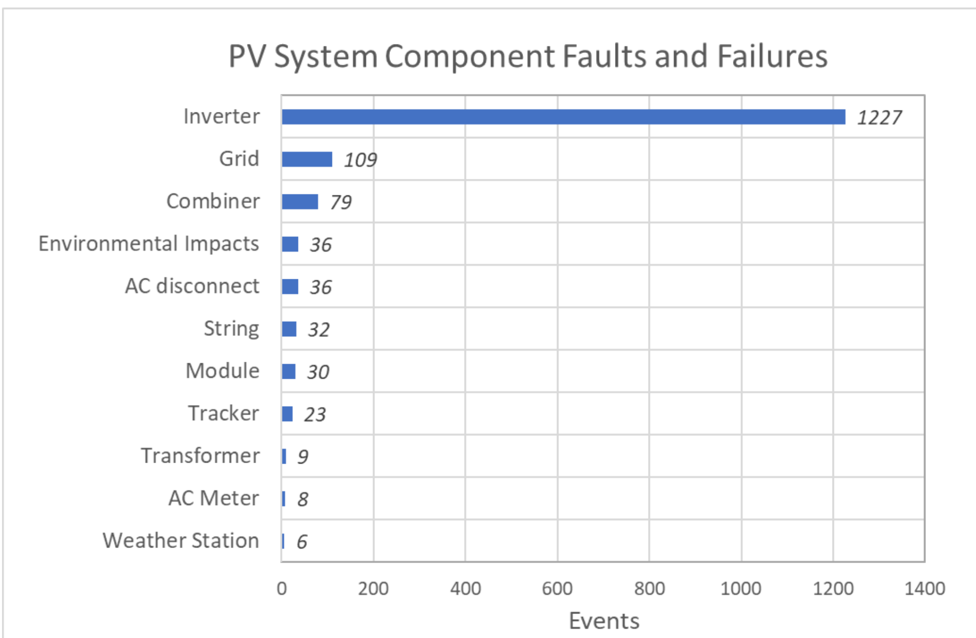

Figure 1. Summary of events (faults and failures) across all portfolios

Figure 2 presents the percentages of the different fault/failures of each component relative to the entire portfolio as shown in Table 2. The differences in the types of faults and failures are reflective of the size, age, location and type of the portfolio. Inverter faults and failures make up the largest share of events at three out of the four portfolios. In Portfolio B, tracker issues made up the largest share of faults and failures. Portfolio D has a relatively large share of grid faults, with most impacting just 2% of the 61 systems in the portfolio. Portfolios C and D represent primarily newer systems compared to A and B. Portfolio C is primarily utility scale, with most systems larger than Portfolio D which is exclusively DG.

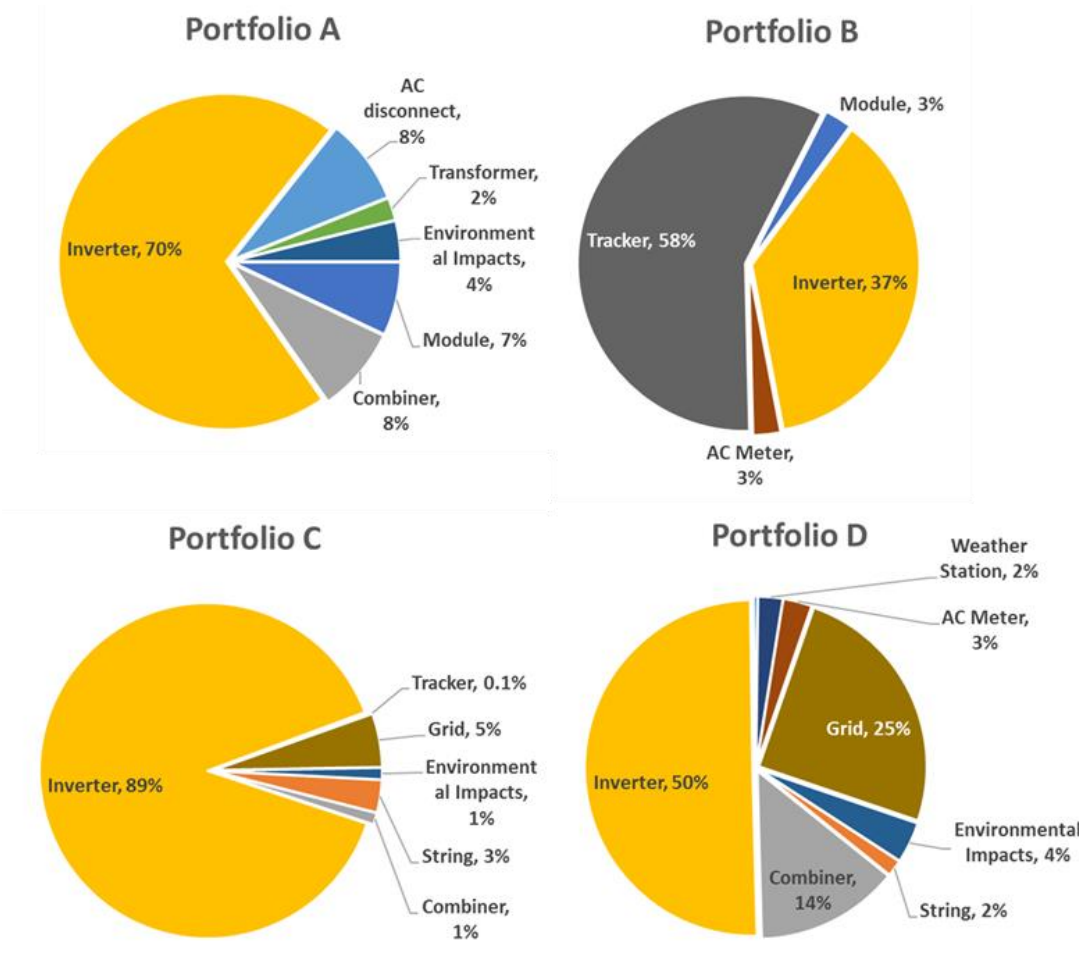

Figure 2. Breakout of component failure percentages by portfolio

As the purpose of this paper is to present reliability distributions developed from the portfolios, we aim first to explain how data owners can develop distributions with their own data and gain insight from that data. These results can then be inputs for O&M cost modeling, or inputs into performance models for assessing impacts based on component reliability assumptions. Future analysis will present a deep dive into the types of issues seen with specific components, and how those compare across portfolios.

3. RELIABILITY DATA ANALYSIS

This section describes how to use maintenance data collected for a specific component and develop both time to failure and time to repair data that can then be fit to a probability distribution. Some of this has been adapted from Klise et al. (2017) which describes how to utilize reliability distributions for simulating PV performance in the SAM implementation of the PV-Reliability Performance Model (PV-RPM).

Looking first at a specific failure, such as an inverter fan issue *specific to that inverter*, for example, will provide the most accurate data to describe that inverter's past behavior. Lumping in other inverter fan issues say for the other three out of the four inverters *at the same site* may provide some similar insight into the behavior, though it may or may not be the same root cause issue. Taking it even further and comparing inverter fan issues *across multiple sites* can add even more uncertainty into the distributions as not every inverter may be having the same level of faults and failures. These differing levels of granularity can provide insight into the type of question being asked and help plan for different maintenance events if a component is suspected to have a serial failure, or poor workmanship is leading to a more isolated incident. That same failure may also be the result of other failures or the cause of subsequent failures. Having good maintenance records can help in the determination of the exact root cause.

3.1. Time to Failure (TTF) and Time to Repair (TTR)

To determine the best fit reliability distribution for failure and repair activities, the time to failure (TTF) and time to repair (TTR) for the event in consideration is calculated. The software described here to develop the distributions may use different conventions than other software, therefore results may differ if using Weibull++ vs. Minitab, for example.

To calculate the TTF, the commissioning time for the PV inverter is subtracted from each downtime start as shown in Figure 3. For this example, all of the data is in days, however this can also be done in hours or in years, depending on the type of analysis platform the data will be utilized within. For the O&M cost model, reliability data must have a time unit of years. In the SAM PV-RPM feature, the reliability data must have a time unit of days. The distribution parameters cannot be converted from hours to another time unit, so it's important to determine what time unit is necessary before making the calculations. In this analysis, we do not distinguish from repairable failures (fuses in an inverter) or non-repairable failures (module junction box falls off). There are many ways to evaluate the reliability state of a component, depending on the type of data available and the type of question being asked.

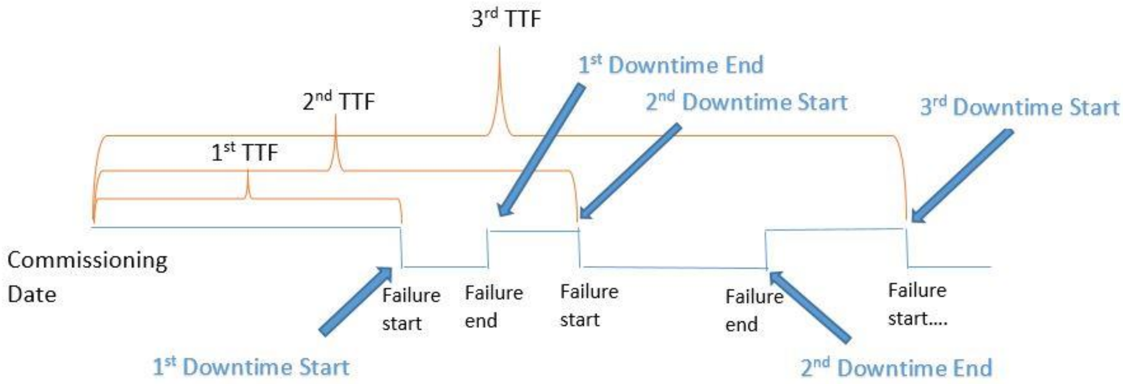

Figure 3. Calculation of Time to Failure using fault or failure times

To calculate the TTR, the difference between each failure end time and the associated failure start time is calculated as shown in Figure 4.

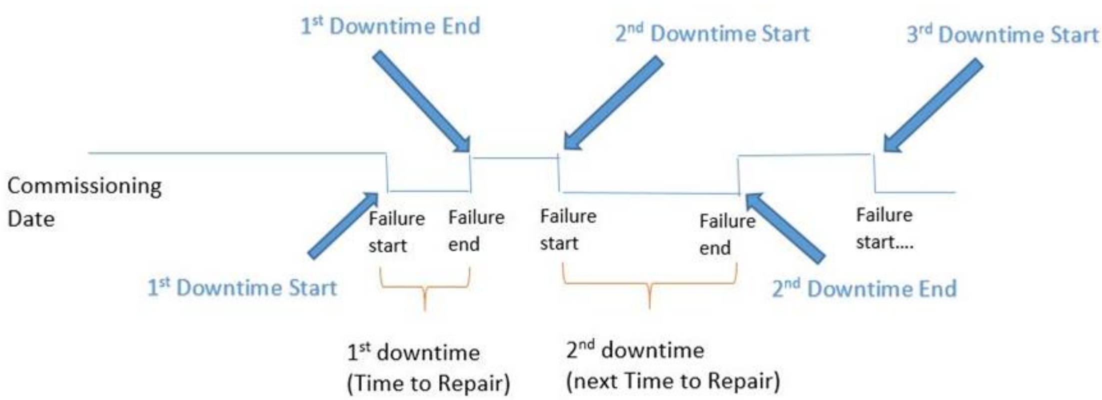

Figure 4. Calculation of Time to Repair using fault of failure times

TTF and TTR results for a hypothetical PV system component are presented in Table 3 as an example of how to take raw event data and develop the correct TTF or TTR tables for developing probability distributions.

Table 3. Example calculation of TTF and TTR

Event	Inverter Commissioning Date	Downtime Start	Downtime End	TTF (days) = Downtime Start – Commissioning Date	TTR(days) = Downtime End – Downtime Start
Fan failure	6/15/2016 0:00	6/30/2016 14:05	7/1/2016 23:59	=6/30/2016 14:05 - 6/15/2016 0:00 = 15.586	= 7/1/2016 23:59 - 6/30/2016 14:05 = 1.412
Fan failure		7/13/2016 13:15	7/13/2016 15:05	=7/13/2016 13:15 - 6/15/2016 0:00 = 28.552	= 7/13/2016 15:05 - 7/13/2016 13:15 = 0.076

Fan failure		7/14/2016 12:10	7/14/2016 14:46	=7/14/2016 12:10 - 6/15/2016 0:00 = 29.507	=7/14/2016 14:46 - 7/14/2016 12:10 =0.108

3.2. Creating Probability Distributions

Once the TTF and TTR are calculated, the best fit reliability distributions can be developed. Probability plots are used to evaluate the fit of each distribution by estimating a cumulative distribution function through plotting the observation against its estimated cumulative probability. Using a program like Minitab, for example, the Individual Distribution Identification function fits the data for up to fourteen different probability distributions. To determine which distributions best fit the data, goodness-of-fit statistics are then evaluated.

The Anderson-Darling statistic (AD) tests whether the sample data comes from a given distribution. For a 'good fit' the AD statistic should be less than one; however, to determine if one distribution is a better fit than another, the AD statistic should be significantly lower than the other distribution. In addition to the AD statistic, the probability value, or 'p-value,' is used. For a given significance level α, (usually 0.05 or 0.10), a p-value $\leq \alpha$ indicates the data does not follow the distribution while a p-value $> \alpha$ indicates that the data has a better fit for the specified distribution. Generally, when comparing different distributions, the highest p-value will indicate the better fitting distribution. Visually one can use the probability plot to further determine if the distribution is a good fit by ensuring that the large majority of the points fall within the confidence intervals and the data follows the straight line of the plot.[1] Using a combination of these three goodness-of-fit evaluations, the best fit probability distribution can eventually be determined by a process of eliminating the distributions that are not a good fit to the underlying data.

As an example, we will consider the TTF to evaluate what failure distributions may have the best fit for an inverter with a faulty fan. A repair distribution will not be developed and shown here, though the same steps can be followed for developing a failure distribution. For this example, it is assumed that all of the events occurred at one site, and impacted every one of the inverters. Figure 5 shows the probability plots for each distribution of interest. The AD statistic for each distribution is greater than one and the p-values are all smaller than 0.05, both indicating that the data is not necessarily a good fit any of the distributions.

[1] http://blog.minitab.com/blog/adventures-in-statistics-2/how-to-identify-the-distribution-of-your-data-using-minitab

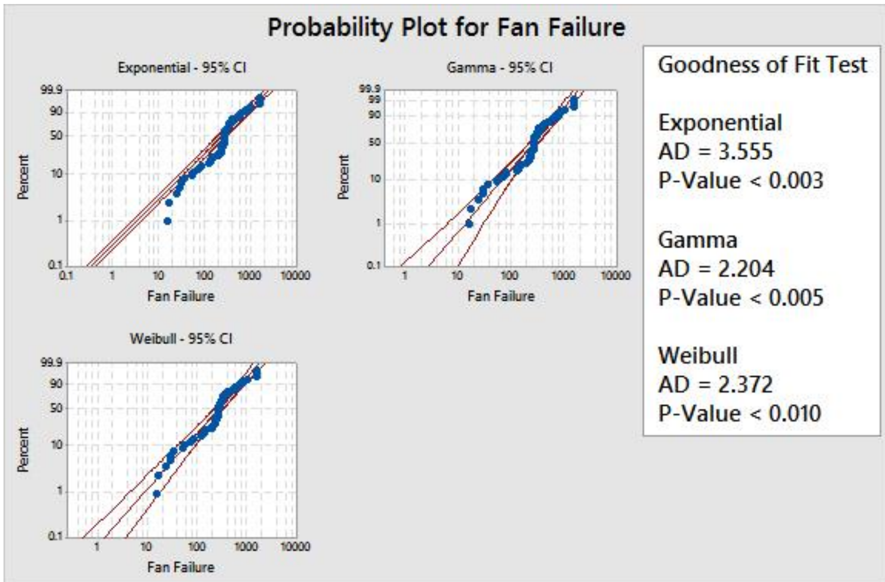

Figure 5. Probability plot of TTF data fit to exponential, gamma and Weibull distributions

Notice that in each plot there appear to be three different slopes to the data. This example combined failures from multiple inverters at the same site. Different slopes may also be indicative of several effects: (1) different underlying failure modes, (2) different failure rates even for the same failure mode (this may in turn depend on many other external and internal factors), (3) different operators and/or different reporting procedures for the same failure mode, and a few others. While not every dataset needs to be separated by failure modes, it is important however to check maintenance logs of different failure events to ensure that they are cataloged correctly. In this case, breaking up the TTF into three separate datasets based on visually inspecting Figure 5 leads to results presented in Figure 6 and Table 3.

Figure 6. Separation of TTF data based on visual inspection of three different slopes in Figure 5 data, fit to exponential, gamma and Weibull distributions

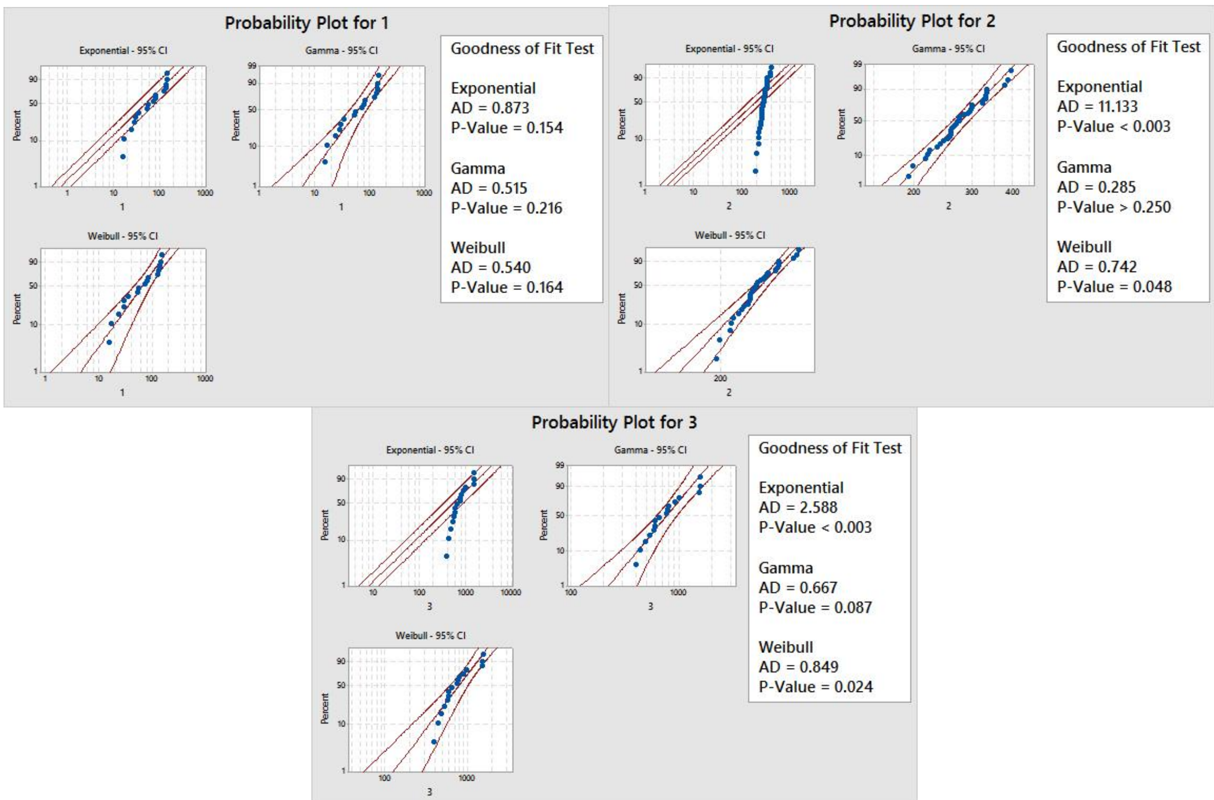

Table 3. Goodness of fit results from Figure 6

Probability Plot 1			
Distribution	*Exponential*	*Weibull*	*Gamma*
AD statistic	0.873	0.540	0.515
p-value	0.154	0.164	0.216
Probability Plot 2			
Distribution	*Exponential*	*Weibull*	*Gamma*
AD statistic	11.133	0.742	0.285
p-value	<0.003	0.048	>0.250
Probability Plot 3			
Distribution	*Exponential*	*Weibull*	*Gamma*
AD statistic	2.588	0.849	0.285
p-value	<0.003	0.024	0.087

In Figure 6 and Table 4, probability plot 1: The exponential distribution can be eliminated first as it has the highest AD statistic and lowest p-value. Comparing the Weibull and gamma distributions, both AD statistics are close so we rely on the larger of the two p-values to determine gamma as the best fit distribution. For probability plot 2, the exponential distribution can again be eliminated right away as the data does not follow the cumulative distribution in the probability plot and does not stay within the confidence intervals. The Weibull distribution can also be eliminated as the p-value is lower than 0.05, leaving gamma as the best fit. Using the same methodology, gamma is determined to be the best fit for the third data set as well. As described in Appendix B, the gamma distribution is one that represents a failure where multiple 'partial' failures occur over time, or when infant mortality is high early for the specific component, then becomes lower with a more constant failure rate over time.

Deconstructing the data allowed for a better fit of the data, indicating that the fan issues at this particular site follow a gamma distribution. This suggests a similar failure mode across all inverters at this site, though a more thorough root cause analysis would have to be completed to confirm this observation.

Table 4. Gamma distribution parameters from best fit of each probability plot

	Alpha	**Beta**
Probability Plot 1	2.10	34.64
Probability Plot 2	35.76	7.75
Probability Plot 3	5.36	153.01

The distributions presented in Table 4 can then be used in the PV-RPM feature in SAM, or in the PV O&M Cost Model (if the time values are first translated into years prior to developing the distributions).

The next section will discuss different failure modes collected by SNL and presented in Appendix A.

4. PORTFOLIO RELIABILITY DISTRIBUTIONS

Appendix A presents summaries of reliability data collected by SNL. This section will describe the data in the appendix and give an example of how to interpret the data.

4.1. Description of Data

Components within the portfolio that have fault/failure and repair distributions include the following:

- PV modules
- DC Combiners
- Inverters
- AC Disconnects
- Grid
- Data Acquisition System
- Programmable Logic Controller
- Hydraulic Cylinders

Currently within the dataset being curated by SNL, there are many failure modes and components that are not included in Appendix A as there are not enough data points to develop a distribution. What is presented are statistics developed where there are more than three events.

Each row with reliability data information has a unique ID which encompasses the component type as well as the general geographic location. West, Southwest, Northeast, etc. Some qualifiers within the name include whether the distribution represents a specific component at that site, a grouping of that same component at one site, or a grouping of that same component across multiple sites.

<u>Vintage/Data Range</u>

This field represents the age of the site when it was commissioned (first date) and the range of dates where data was collected. For example, the first row of reliability data in this appendix has a value of 2001-2004. This data was collected from the original commissioning of the site in 2001 up through 2004. Other rows that only show the Data Range do not have the original commissioning date as the distributions represent systems with different commissioning dates.

The more common distributions that end up having the best fit for faults and failures in the SNL dataset include the Weibull, Gamma, Normal and Exponential. For repair events, the most common in the SNL dataset include Normal, Lognormal and Exponential.

<u>Component Size</u>

This lists the approximate size of the component that is described by the distribution, either in watts or kilowatts for inverters or modules and listed in the cell for other components.

<u>System Size/Site Range</u>

Here, the approximate size of the PV system is shown for the component in question. For larger portfolios, the Site Range is given.

Failure Distribution

The best fit failure distribution generated using steps in Section 2 is presented here. There are typically two parameters that define the shape of the distribution, with the exception of exponential distributions, which have one parameter. The time unit is also presented, which is important if using data in the PV O&M Cost Model or PV-RPM in SAM. More detail describing in general terms the types of distributions used in fault/failure analysis is presented in Appendix B.

Repair Distribution

The repair distribution describing the probability of repairing that specific component is presented here. The type, along with the parameters that describe the distribution and time unit are also shown. These take on a different shape and distribution than the failure distribution as the repairs are more likely to happen soon after the fault/failure than later. Parameters for repair distributions may depend on a variety of internal and external factors, such as availability of qualified personnel, availability of parts in stock, etc.

Failure Rate

The failure rate is presented as number of failures in 1 Million hours. It is calculated as a function of the total operating hours of the component since commissioning, using a stop date of December 11, 2017. The convention is that the failure rate reflects a component in the constant failure mode phase, where infant mortality issues have been eliminated. There are only a few values calculated here and caution should be exercised when interpreting this data as the interval may not necessarily be reflective of the component having a constant failure rate.

MTBF

The mean time between failures represents the total time from the start of the first fault/failure event up through the stop date of December 11, 2017 divided by the total number of failures. As with interpreting the failure rate, the same caution should be applied when interpreting this value as it should refer to a component undergoing a constant failure rate, however the data presented here may not always satisfy that condition.

Notes and References

Footnotes are presented for the reader describing sources for some of the data, or caveats when considering different failure distributions.

General Notes

This provides more details on the type of failure or number of components used to develop the distribution.

4.2. Interpretation Example

Using data from Appendix A, we provide an example of how to interpret the failure and repair distribution parameters (Table 5). Three different events are shown along with system details, and both failure and repair distributions.

Table 5. Probability distribution parameters for different fault/failure events

			Fault/Failure Distribution				Repair Distribution			
Example	**Component & Location**	**Failure Type**	**Type**	**Shape / Mean**	**Scale / Stdev.**	**Time Unit**	**Type**	**Mean**	**Stdev.**	**Time Unit**
1	One Inverter at a site in the Eastern U.S.	Fuse failures	Weibull-2	13.03	714.27	day	Lognormal	0.6507	0.5431	day
2	One Inverter at a site in the Eastern U.S.	Tripping and resetting due to arc faults	Normal	256.979	148.56	day	Lognormal	-0.1181	1.3368	day
3	One Site in the Eastern U.S.	Recloser tripping on grid side	Weibull-2	1.36296	332.93	day	Lognormal	-1.7275	1.1695	day

Example 1

In this example, the highest probability of an inverter fuse failure peaks at just after 700 days of operation with a right-skewed distribution (Figure 7).

There is a higher probability the fuse will be replaced between 1.5 days after failure as shown in this left-skewed distribution. There is only a 20% chance that the repair will happen 3 days after the event, suggesting these are responded to soon after the event.

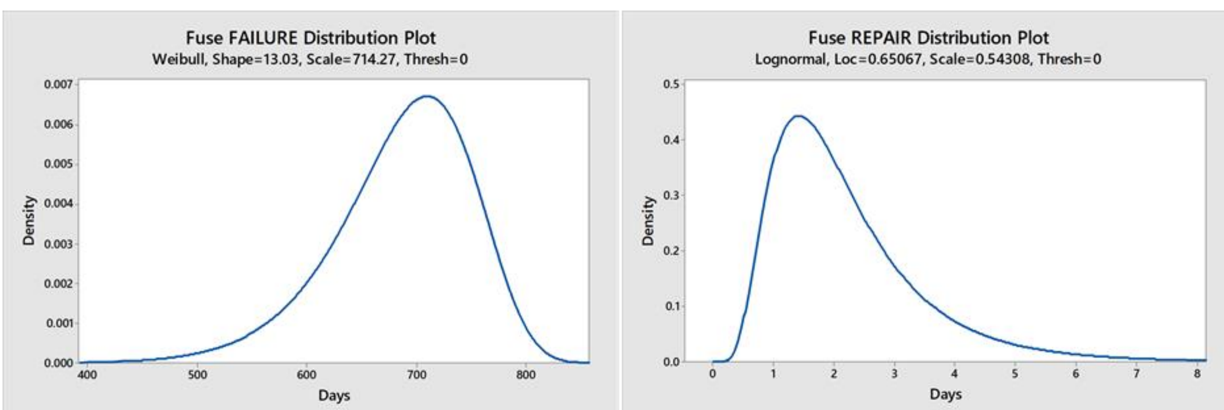

Figure 7. Failure and repair distribution example for fuse failure

Example 2

In this example, the arc fault events were observed to follow a normal distribution, with the highest probability just before 300 days of operation. These occur in the balance-of-system DC side, and are detected by the inverter (Figure 8). It is not known if these events are due to workmanship or other external factors. Different failure modes will result in different failure distribution shapes.

The repair happens very quickly after the arc fault as shown by the highest probability of a repair event around 0.15 days, as the inverter resets (software reset) after the fault event. Arc fault events that take longer to address (two days) likely require a manual reset have a 27% probability of happening 2 days after the event, suggesting most resets occur shortly after the event.

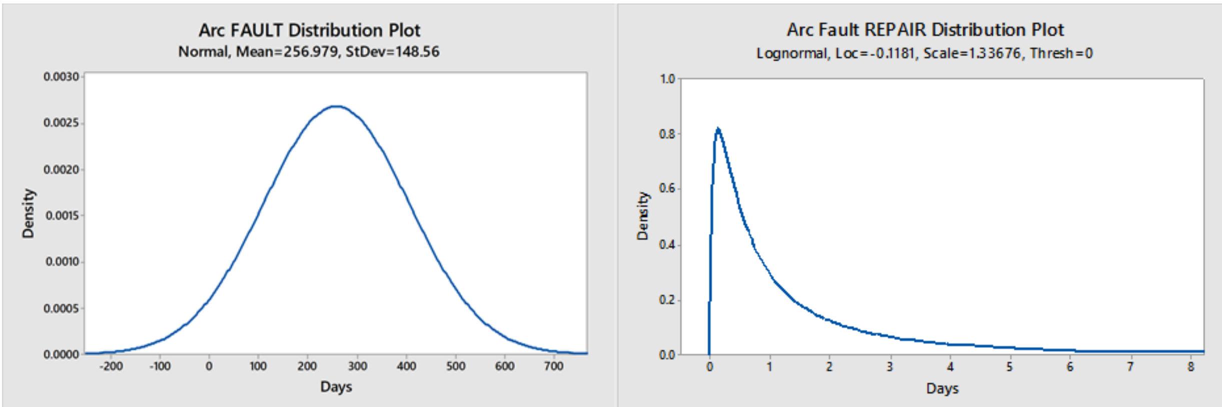

Figure 8. Failure and repair distribution example for arc fault tripping the inverter

<u>Example 3</u>

In this example, the highest probability of a recloser tripping on the utility side of this system occurs around 125 days of operation, and tails off slowly as shown in this left-skewed distribution. As this operator has the ability to remotely re-set the recloser, the repair distribution shows the highest probability of repair at 0.04 days, or ~ 1 hour after the event (Figure 9).

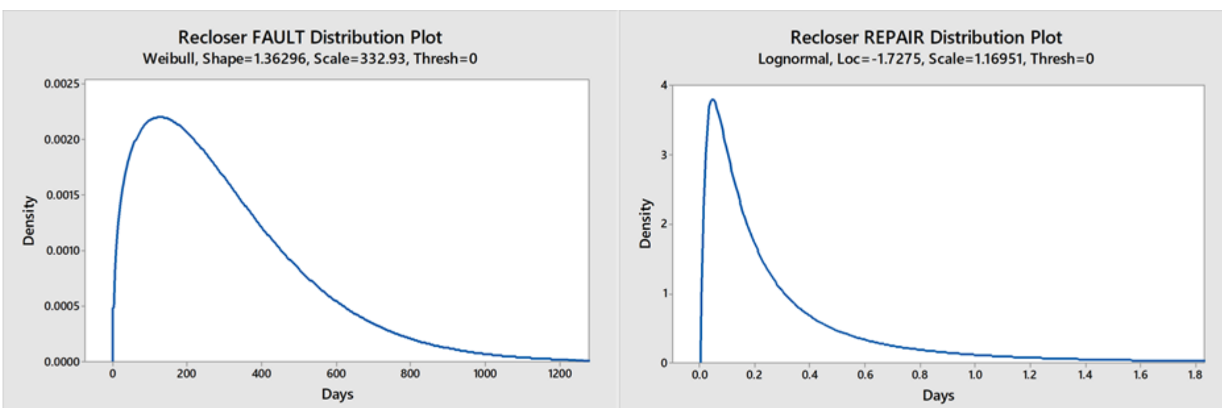

Figure 9. Failure and repair distribution example for utility recloser issue

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APPENDIX A: RELIABILITY DISTRIBUTION PARAMETERS DEVELOPED FROM PORTFOLIO FAULT AND FAILURE DATA

				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
PV Module	Vintage/Data Range	Component Size (W DC)	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Mean	Stdev.	Time Unit			Notes and References	General Notes
ID_TEP_module (Southwest)	2001-2004	300	3.5	Weibull-2	0.28	5.00E+12	day	Lognormal-n	-1.37	13.11	day			i, 1,2	In reference 2, discussion on lightning as cause for some module failures. Replacement Rate was 5 in 10,000 per year for first 5 years.
				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
DC Combiner	Vintage/Data Range	Component Size DC	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Mean	Stdev.	Time Unit			Notes and References	General Notes
ID_TEP_Dccombiner (Southwest)	2001-2004	Unk.	3.5	Weibull-2	0.51	1.20E+06	day	Lognormal-n	-0.98	2.07	day			i, 1,2,3	No discussion on what caused failure for DC combiner boxes. In Reference 2, these are referred to as "Row Boxes"
				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
Inverter	Vintage/Data Range	Component Size (kW DC)	System Size (MW DC)	Type	lambda/Shape	Scale	Time Unit[iii]	Type	Shape/Mean	Scale/Stdev.	Time Unit			Notes and References	General Notes
ID_TEP_Inverter_lightning (Southwest)	2001-2004	100 or 150	3.5	Exponential-1	0.00022		day	Weibull-2	0.73	10.8	day			ii, 1,2,3	Damage from lightning. PCU card most often replaced. Lightning arrestors added after large storms in 2003
ID_TEP_Inverter_All (Southwest)	2001-2004	100 or 150	3.5	Exponential-1	0.00278		day	Lognormal-n	-4.25	2.27	day			i, ii, 1,2,3	Combination of all inverter faults and failures.
	Vintage/Data Range	Component Size (kW DC)	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Mean	Stdev.	Time Unit				
ID_VS_Inverter (Southwest)	2008-2009	250	0.6 to 1.1	Weibull-2	111.0869	40655.35	hour	Lognormal	1.5026	2.17808	day			N/A	Combination of faults that were reset, and matrix boards that were replaced
ID_utility_a_inverter_fan	Data Range	Component Size (kW DC)	Site Range (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Mean/lambda	Stdev.	Time Unit			Notes and References	General Notes
Specific Inverter 1 (among all sites)	2013-2015	500-1500	15 to 25	Weibull-2	1.16806	607.8768	day	Lognormal	1.68105	6.43975	day				Fan faults/failures
Specific Inverter 2 (among all sites)	2013-2015	1000-1500	2 to 60	Weibull-2	1.48506	93.68915	day	Weibull-2	0.806953	2.36561	day				Fan faults/failures
All Inverters at One Site (West)	2013-2015	500-1500	2 to 5	Weibull-2	12.34901	273.54862	day	Lognormal	3.86093	11.9357	day				Fan faults/failures
Specific Inverter ID at One Site (West)	2013-2015	500-1500	15 to 25	Weibull-2	5.08414	29.53872	day	Lognormal	1.64102	5.84476	day				Fan faults/failures
All Inverters Eastern U.S.	2013-2015	500-1500	3 to 5	Weibull-2	1.96913	866.07292	day	Weibull-2	0.762432	3.66232	day				Fan faults/failures within 7 sites
Specific Inverter 1 (among all sites)	2013-2015	500-1500	15 to 25	Weibull-2	1.16806	1.66542	year	Weibull-2	3.76474	0.00034	year				Fan faults/failures
Specific Inverter 2 (among all sites)	2013-2015	1000-1500	2 to 60	Weibull-2	5.09336	0.07858	year	Weibull-2	2.22282	0.0005	year				Fan faults/failures
All Inverters at One Site (West)	2013-2015	500-1500	2 to 5	Weibull-2	12.34901	0.749448	year	Normal	0.000421	0.003614	year				Fan faults/failures
Specific Inverter ID at One Site (West)	2013-2015	500-1500	15 to 25	Weibull-2	12.42656	0.00595	year	Normal	0.003363	0.003614	year				Fan faults/failures
All Inverters Eastern U.S.	2013-2015	500-1500	3 to 5	Weibull-2	1.96913	2.3728	year	Lognormal	0.020099	0.088043	year				Fan faults/failures within 7 sites
ID_utility_a_inverter_IGBT	Data Range	Component Size (kW DC)	Site Range (MW DC)	Type	Shape/Alpha	Scale/Beta	Time Unit[iii]	Type	Shape/Mean/lambda	Scale/Stdev.	Time Unit			Notes and References	General Notes
All Inverters at One Site (East)	2013-2015	500-1500	2 to 5	Weibull-2	7.16041	901.10575	day	Weibull-2	2.56765	12.80014	day				IGBT failures
Specific Inverter (among all sites)	2013-2015	250-1000	1-25	Gamma	10.69271	71.11886	day	Weibull-2	2.55113	12.61116	day				IGBT failures, 9 sites
All Inverters Eastern U.S.	2013-2015	500-1500	2-10	Weibull-2	1.47374	799.39363	day	Exponential-1	9.49382	N/A	day				IGBT failures, 5 sites
All Inverters Western U.S.	2013-2015	500-2000	2-35	Weibull-2	1.351	589.60393	day	Weibull-2	1.43987	9.73814	day				IGBT failures, 8 sites
All Inverters at One Site (East)	2013-2015	500-1500	2 to 5	Weibull-2	23.67141	0.09703	year	Weibull-2	2.56765	0.03507	year				IGBT failures
Specific Inverter (among all sites)	2013-2015	250-1000	1-25	Gamma	10.69271	0.19485	year	Weibull-2	2.55113	0.03455	year				IGBT failures, 9 sites
All Inverters Eastern U.S.	2013-2015	500-1500	2-10	Weibull-2	1.4374	2.19012	year	Weibull-2	1.26342	0.02792	year				IGBT failures, 5 sites
All Inverters Western U.S.	2013-2015	500-2000	2-35	Weibull-2	1.351	1.61535	year	Normal	0.024561	0.015101	year				IGBT failures, 8 sites
ID_utility_a_inverter_cooling	Data Range	Component Size (kW DC)	Site Range (MW DC)	Type	Shape/Alpha	Scale/Beta	Time Unit[iii]	Type	Mean/Shape	Stdev./Scale	Time Unit			Notes and References	General Notes
All Inverters at One Site (West)	2013-2015	500-1500	15 to 30	Weibull-2	7.37307	376.81404	day	Lognormal	3.4111	11.6452	day				Cooling issues
Specific Inverter (among all sites)	2013-2015	500-2000	2 to 50	Weibull-2	2.04092	395.13783	day	Lognormal	1.91479	4.47639	day				Cooling issues, 8 sites
Specific Inverter (among all sites)	2013-2015	250-1000	2 to 25	Weibull-2	0.78454	354.46402	day	Weibull-2	0.83494	1.71179	day				Cooling issues, 4 sites
All Inverters Eastern U.S.	2013-2015	500-1500	2 to 10	Weibull-2	0.92279	1.797	day	Weibull-2	5.67827	518.54123	day				Cooling issues, 3 sites
All Inverters Western U.S.	2013-2015	500-2000	2 to 50	Gamma	2.33176	127.92907	day	Weibull-2	0.5935	0.73041	day				Cooling issues, 12 sites
All Inverters at One Site (West)	2013-2015	500-1500	15 to 30	Weibull-2	6.00263	1.10193	year	Weibull-2	0.76662	0.00441	year				Cooling issues
Specific Inverter (among all sites)	2013-2015	500-2000	2 to 50	Weibull-2	2.0925	1.09703	year	Weibull-2	0.80727	0.00407	year				Cooling issues, 8 sites
Specific Inverter (among all sites)	2013-2015	250-1000	2 to 25	Weibull-2	0.78454	0.97113	year	Weibull-2	0.90135	0.00579	year				Cooling issues, 4 sites
All Inverters Eastern U.S.	2013-2015	500-1500	2 to 10	Weibull-2	5.91295	0.21954	year	Weibull-2	0.92279	0.00492	year				Cooling issues, 3 sites
All Inverters Western U.S.	2013-2015	500-2000	2 to 50	Gamma	2026694	0.36088	year	Weibull-2	0.60181	0.00205	year				Cooling issues, 12 sites
ID_utility_a_inverter_cycling	Data Range	Component Size (kW DC)	Site Range (MW DC)	Type	Lambda/Shape	Scale	Time Unit[iii]	Type	Mean/Shape	Stdev./Scale	Time Unit			Notes and References	General Notes
All Inverters at One Site (West)	2013-2015	1000-1500	10 to 15	Exponential-1	83.066		day	Lognormal	0.241061	0.0496306	day				Power cycling
All Inverters at One Site (West)	2013-2015	1000-1500	15 to 25	Weibull-2	4.10774	353.63	day	Lognormal	5.15977	30.0369	day				Power cycling
Specific Inverter (among all sites)	2013-2015	1000-1500	2 to 25	Weibull-2	3.09197	418.13464	day	Lognormal	4.73865	4.41415	day				Power cycling, 11 sites
All Inverters Eastern U.S.	2013-2015	1000-1500	2 to 10	Weibull-2	5.67827	518.54123	day	Weibull-2	0.89665	2.48832	day				Power cycling, 4 sites
All Inverters Western U.S.	2013-2015	1000-1500	3 to 25	Weibull-2	1.70403	294.05056	day	Weibull-2	2.12009	0.23041	day				Power cycling, 7 sites
All Inverters at One Site (West)	2013-2015	1000-1500	10 to 15	Weibull-2	1.37223	0.35031	year	Weibull-2	0.000649	0.000145	year				Power cycling
All Inverters at One Site (West)	2013-2015	1000-1500	15 to 25	Weibull-2	4.10774	0.96886	year	Lognormal	0.014136	0.082293	year				Power cycling
Specific Inverter (among all sites)	2013-2015	1000-1500	2 to 25	Weibull-2	3.09197	1.14557	year	Weibull-2	2.29627	0.00069	year				Power cycling, 11 sites
All Inverters Eastern U.S.	2013-2015	1000-1500	2 to 10	Weibull-2	19.30408	0.06803	year	Weibull-2	0.89665	0.00682	year				Power cycling, 4 sites
All Inverters Western U.S.	2013-2015	1000-1500	3 to 25	Weibull-2	2.06976	0.34899	year	Weibull-2	2.12	0.00063	year				Power cycling, 7 sites
ID_utility_a_inverter_grid	Data Range	Component Size (kW DC)	Site Range (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Shape	Scale	Time Unit			Notes and References	General Notes
Specific Site Specific Inverter Western U.S.	2013-2015	500-2000	2 to 50	Weibull-2	1.20783	515.783	day	Weibull-2	0.62678	1.61112	day				
ID_utility_a_inverter_PM	Data Range	Component Size (kW DC)	Site Range (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Shape/Mean	Scale/Stdev.	Time Unit			Notes and References	General Notes
Specific Site Specific Inverter Western U.S.	2013-2015	500 - 1500	5-15	Weibull-2	107.704	516.797	day	Weibull-2	3.25542	0.06094	day				Preventative Maintenance
Specific Site Specific Inverter Western U.S.	2013-2015	1000 - 1500	10-15	Weibull-2	11385.4	340.579	day	Normal	0.03559	0.007908	day				
ID_DG_a_inverter_fuse_hardware	Vintage/Data Range	Component Size (kW DC)	Site Range (kW DC)	Type	Mean/Shape	Stdev./Scale	Time Unit[iii]	Type	Mean/Lambda	Stdev.	Time Unit			Notes and References	General Notes
Specific Inverter Entire Portfolio Eastern U.S.	2011-2017	50 - 150	105-450	Lognormal	7.38327	0.16971	day	Lognormal	0.30378	0.82292	day			iii	Fuse faults
Specific Inverter Entire Portfolio Eastern U.S.	2014-2017	50 - 150	105-450	Normal	498.23	277.15	day	Lognormal	0.30378	0.82292	day			iii, iv	fuse and hardware faults
Specific Inverter(s) at One Site Eastern U.S.	2014-2017	50 - 150	200	Weibull-2	13.03	714.27	day	Lognormal	0.65067	0.54308	day	68.45	147.16	iii, iv	fuse faults
Specific Inverter(s) at One Site Eastern U.S.	2014-2017	50 - 150	350	Normal	510.72	325.8	day	Lognormal	0.25971	1.14308	day	68.45	62.75	iii, iv	fuse and amperage faults
Specific Inverter(s) at One Site Eastern U.S.	2014-2017	50 - 150	450	Lognormal	6.11	0.65	day	Lognormal	0.41589	0.37965	day	51.33	44.10	iii, iv	fuse and hardware faults
Specific Inverter(s) at One Site Eastern U.S.	2014-2017	50 - 150	105	Normal	400.55	21.66	day	Exponential-1	1.75		day	102.67	294.92	iii, iv	Fuse and hardware faults
ID_DG_a_inverter_ground_arc_fault	Vintage/Data Range	Component Size (kW DC)	Site Range (kW DC)	Type	Mean/Location	Stdev./Scale	Time Unit[iii]	Type	Location	Scale	Time Unit			Notes and References	General Notes
Inverter A Eastern U.S.	2014-2017	20	175	Normal	343.30	86.12971	day	Lognormal	-0.21526	1.65686	day	228.10	110.83		arc fault somewhere on DC side
Inverter B Eastern U.S.	2014-2017	20	175	Normal	256.97917	148.56025	day	Lognormal	-0.11811	1.33676	day	114.05	191.11		arc fault somewhere on DC side
Inverter C Eastern U.S.	2014-2017	20	175	Normal	323.42188	104.96245	day	Lognormal	-0.41328	1.64365	day	228.10	93.00		arc fault somewhere on DC side
Inverter D Eastern U.S.	2014-2017	20	175	Lognormal	5.90963	0.44702	day	Lognormal	-0.04817	1.49318	day	228.10	85.83		arc fault somewhere on DC side

				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
AC Disconnect	Vintage/Data Range	Component Size	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Shape	Scale	Time Unit			Notes and References	General Notes
ID_TEP_ACdisconnect (Southwest)	2001-2004	480 V	3.5	Weibull-2	0.35	11000	day	Weibull-2	0.71	1.4	day			ii, 1,2,3	high contact resistance due to grease attracting dust
				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
HV Transformer	Vintage/Data Range	Component Size	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Shape	Scale	Time Unit			Notes and References	General Notes
ID_TEP_HV_Transformer (Southwest)	2001-2004	480/34.5 kV	3.5	Weibull-2	0.58	7100	day	Weibull-2	0.53	1.36	day			ii, 1,2,3	
				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
Grid	Vintage/Data Range	Component Size	System Size (MW DC)	Type	Mean	Stdev.	Time Unit[iii]	Type	Shape	Scale	Time Unit			Notes and References	General Notes
ID_TEP_Grid (Southwest)	2001-2004	N/A	3.5	Lognormal-n	3.62	1.7	day	Weibull-2	1.07	0.16	day			i, ii, 1,2,3	
ID_DG_a_recloser_trip_grid	Vintage/Data Range	Component Size	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Mean	Stdev.	Time Unit			Notes and References	General Notes
One Site Eastern U.S.	2015-2017	N/A	2.0	Weibull-2	1.36296	332.93	day	Lognormal	-1.72747	1.16951	day	1134.89	34.56	i, iii	On utility side
				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
Data Acquisition System	Vintage	Component Size	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Mean	Stedv.	Time Unit			Notes and References	General Notes
ID_VS_DAS (Southwest)	2008-2009	N/A	0.6 to 1.1	Weibull-2	8.34817	40223.13	hour	Normal	3.24208	106.529	hour				power supply issue
				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
Programmable Logic Controller	Vintage	Component Size	System Size (MW DC)	Type	Shape	Scale	Time Unit[iii]	Type	Shape	Scale	Time Unit			Notes and References	General Notes
ID_VS_PLC_CYL (Southwest)	2008-2009	N/A	0.6 to 1.1	Weibull-2	12.30621	30338.73	hour	Weibull-2	0.47499	30.1237	hour				PLC for hydraulic cylinder operation
				Failure Distribution				Repair Distribution				Failure Rate 10^6 hrs	MTBF (days)		
Hydraulic Cylinders	Vintage	Component Size	System Size (MW DC)	Type	Mean	Stdev.	Time Unit[iii]	Type	Shape	Scale	Time Unit			Notes and References	General Notes
ID_VS_CYL (Southwest)	2008-2009	N/A	0.6 to 1.1	Normal	38687.03	3280.432	hour				hour				

Notes:

i If using LOGNORMAL-N, you need Mean and Stdev. of underlying normal distribution. Since most users will only have the Mean and Stdev. of actual distribution, the SAM implementation needs to translate from Mean and Stdev. to Mean and Error Factor to be able to use LOGNORMAL. If you have negative values in your lognormal parameters, then use LOGNORMAL-N, which means you likely have the Mean and Stdev. of the underlying normal distribution.

ii The Inverter mentioned for the site was 150 kW, however no historic documentation can be found for the manufacturer that a 150 kW inverter was ever made. It was possible that the inverter was never commercially available outside of this one power plant. Also, when setting up a performance model, 100 kW was used instead and has a better electrical match than a 150 kW inverter from a different manufacturer. iii iv v vi

iii *Hourly* or *Daily* time units can be used in the PV-RPM Model in SAM

Year time unit can be used in the NREL/SunSpec O&M Cost Model

iv Later commissioning start date due to records unavailable between commissioning and 2014.

References

1 Moore, L.M. and H.N. Post, 2007, Five Years of Operating Experience at a Large, Utility-scale Photovoltaic Generating Plant, Prog. Photovoltaic: Res. Appl. DOI: 10.1002/pip.800

2 Collins, E., M. Dvorack, J. Mahn, M. Mundt, and M. Quintana, 2009, A Reliability and Availability Analysis of a Fielded Photovoltaic System. 34th IEEE PVSC, Philadelphia, PA, June 7-12, 2009.

3 Klise, G.T, O. Lavrova, and J. Freeman, 2017, Validation of PV-RPM Code in the System Advisor Model, SAND2017-3676, Sandia National Laboratories, Albuquerque, NM.

APPENDIX B: PROBABILITY DISTRIBUTIONS USED TO DEVELOP FAULT AND FAILURE DISTRIBUTIONS

1. UNIFORM

The uniform distribution is one that would likely not be utilized for reliability analysis of photovoltaic systems as it has a constant probability where there is an equal likelihood that an event would occur over the entire distribution. Figure A-1 below shows a pdf of a uniform distribution with a minimum value of 2 and a maximum value of 6.

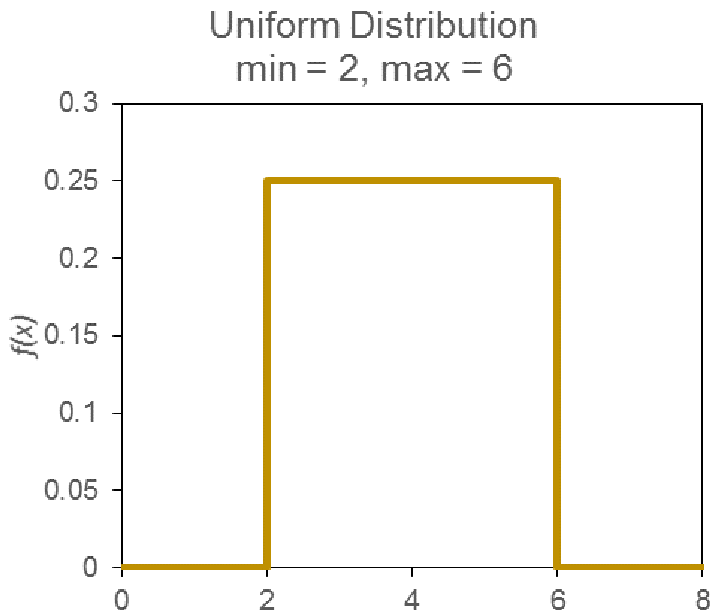

Figure A-1. Uniform Distribution

2. NORMAL

A normal (Gaussian) distribution is typically represented by the classic bell shaped curve, where the mean (mu or μ) is the location where the apex of the pdf occurs and the standard deviation (sigma or σ) defines the height of the distribution, where 68% of the data that is sampled from the distribution will be found (Figure A-2).

Normal distributions are used when a component is expected, or known to have an increasing failure rate over time followed by a reduced failure rate later in life, for a mechanical system where there is external stress that creates a wearout effect, and for failures as a result of chemical processes that can result in corrosion, for example (Pham, 2006).[2] A concern about using a normal distribution for reliability analysis is that if the standard deviation is too large, then negative time values may result. If the standard deviation is small, this can prevent that behavior.[3]

[2] Pham, H., (2006), "System Software Reliability," Chapter 2 – System Reliability Concepts. Springer, 440 p.
[3] http://reliawiki.org/index.php/The_Normal_Distribution

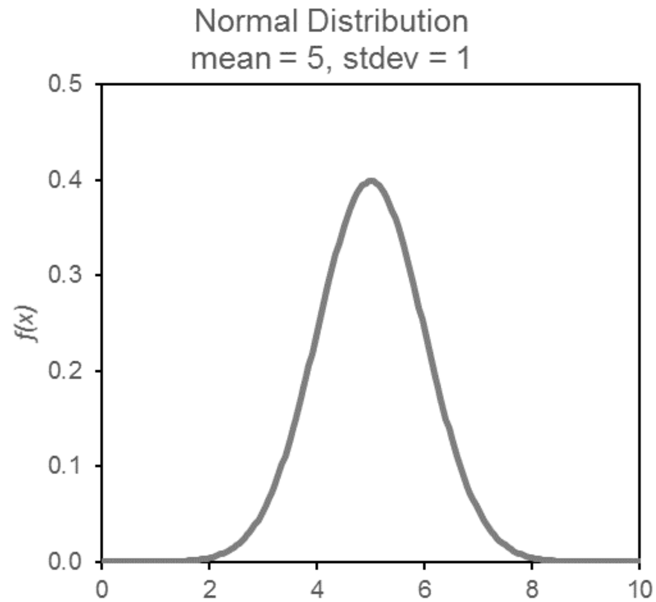

Figure A-2. Normal Distribution

Figure A-3 shows what happens when the mean is held constant but the standard deviation increases. The distribution peak moves down as the first standard deviation spreads out further to the left and right. The left tail of the flatter normal distribution shows where negative time values may result.

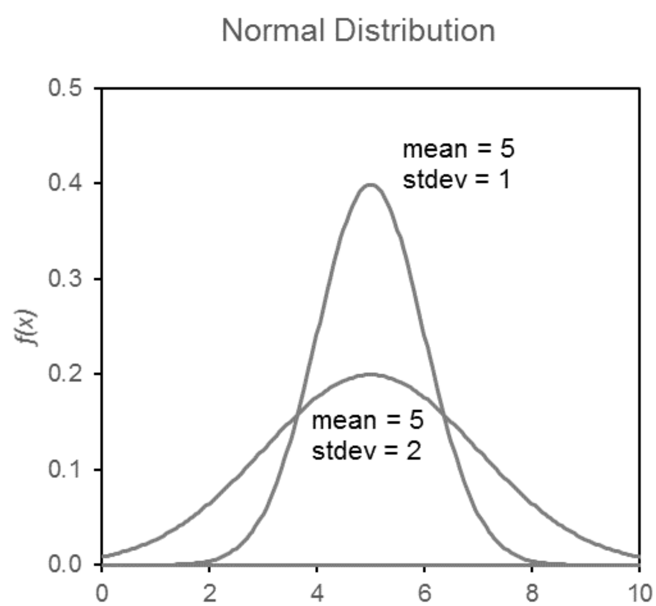

Figure A-3. Normal Distribution: Change in Standard Deviation

3. LOGNORMAL

The lognormal distribution is useful for approximating component behavior due to fatigue related stress. This type of distribution is also good for modeling repairable systems, which can lead to time to repair (TTR) estimates and repair distributions using maintainability data. When the data is positively skewed, it is possible to take the log of the data to approximate a normal distribution.

When using the PV-RPM feature in SAM, the SNL LHS function as implemented in SAM requires mean and error factor inputs into the lognormal function. The Lognormal-n function requires the mean and standard deviation of the UNDERLYING normal distribution. However, we anticipate that most users will have the mean and standard deviation of the actual lognormal distribution. Therefore, the LHS function implemented in the PV-RPM script translates from input mean and standard deviation to the error factor before calling the lognormal LHS function. The translation equations used can be found at https://dakota.sandia.gov/content/latest-reference-manual, Keywords>Variables>lognormal_uncertain. Depending on the software used to develop the distribution, some lognormal inputs may have a negative value for the mean. The use of lognormal-n allows a negative mean value to be processed.

The parameters used for a lognormal distribution are the mean (mu or μ) and standard deviation (sigma or σ). Figure A-4 provides four different plots of the lognormal distribution to show how changing the mean and standard deviation impacts the spread and skewness of the pdf. In this case, the solid line plots have the same mean, and increasing the standard deviation from 0.5 to 1 results in a shorter peak that then shifts left on the x-axis becoming more right skewed. When the standard deviation is held constant as shown with the dotted lines, the distribution flattens out more as the mean increases, becoming less right skewed.

Considering a failure event that could be expressed by this distribution, there is an increased likelihood that the event will happen early on during the component lifetime, though over time, the probability that it will happen starts decreasing, either sharply, or more gradually. Using this as a repair distribution, there is a high likelihood that the failure will be fixed soon after the event rather than much later, such as nuisance tripping events for an inverter.

Much of what can be represented by a lognormal distribution can also be approximated with a Weibull distribution.

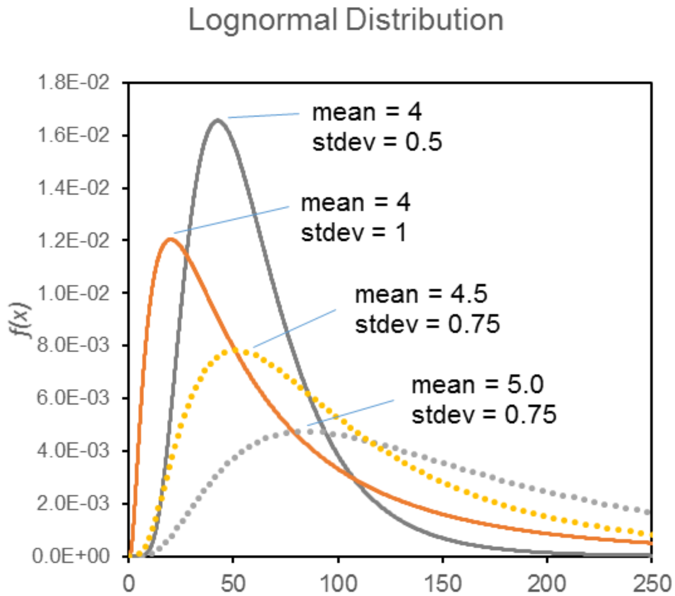

Figure A-4. Lognormal Distribution: Change in Mean and Standard Deviation

4. TRIANGULAR

This type of distribution is used when the component's behavior may be known, but there isn't a large enough dataset to develop a representative distribution. This allows the user the ability to define a minimum, maximum and most probable value. The triangle can be symmetric, or skewed either left or right. If using the PV-RPM feature in SAM, the implementation asks for variables A, B and C in order of input into the function. A is the minimum x value where y = 0. B is the 'mode' or peak of the triangle. C is the maximum x value where y = 0.

The example below shows a non-symmetrical triangle, with a minimum time of 0 and maximum of 6, with the highest probability of an event at time 2.

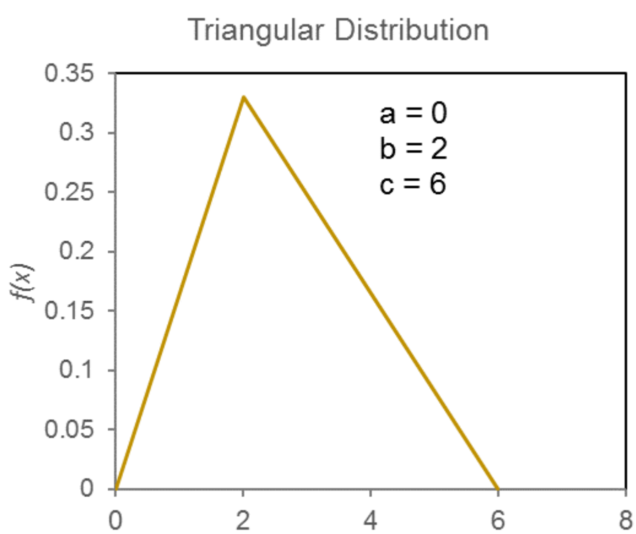

Figure A-5. Triangular Distribution

5. GAMMA

A gamma distribution is one that can be used to represent a failure event where multiple 'partial' failures occur over time, resulting in complete failure of the component. It can also describe infant mortality failures that occur on the left hand side of the 'bathtub curve'. It is not however a common distribution used for 'common failure mechanism.[4]

However, in our analysis presented in Section 3, the gamma distribution is the best fit for the data.

Alpha and Beta parameters are used in the Gamma distribution. Examples of holding the alpha constant and beta constant are presented in Figure A-6. When holding the alpha constant, an increasing beta lowers the peak and shifts it to the right. When holding beta constant, increasing alpha also lowers the peak and shifts it to the right.

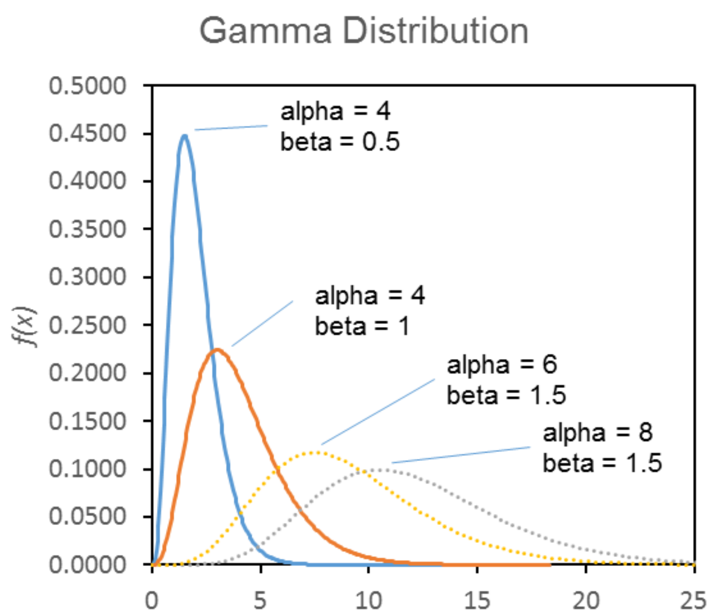

Figure A-6. Gamma Distribution: Change in Alpha and Beta

6. POISSON

A Poisson distribution is typically used in reliability settings to represent discrete events with a constant failure rate over a given time interval. This distribution is essentially a binomial distribution when there are low occurrence probabilities. Lightning events impacting a PV system can be modeled using a Poisson distribution. Spare parts analysis can also be done using a Poisson distribution, if a constant failure rate is already known.[5]

The symbol used in the Poisson distribution is Lambda (Shape parameter) which can be thought of the expected or average number of events. Increasing Lambda from 0 results in a shift of the distribution to the right, and a lowering of the peak value.

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[4] http://reliawiki.org/index.php/The_Gamma_Distribution
[5] https://src.alionscience.com/pdf/POIS_APP.pdf

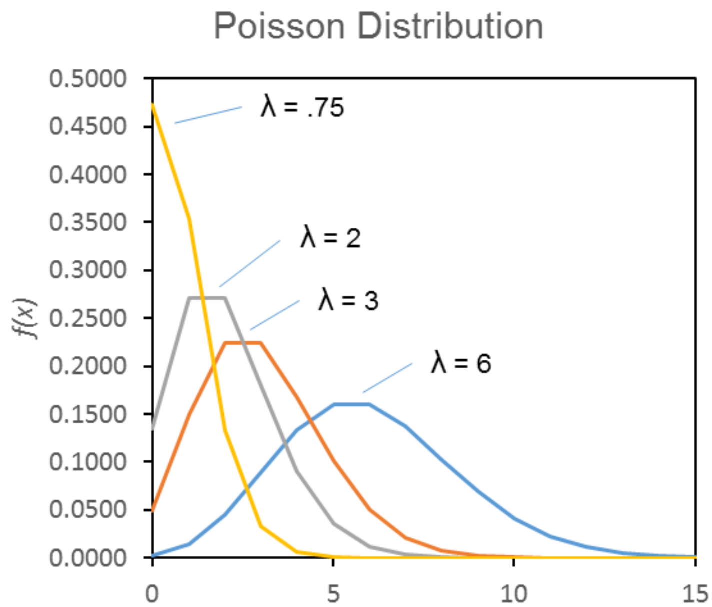

Figure A-7. Poisson Distribution: Change in Lambda

7. BINOMIAL

Like Poisson, integer values are used as random numbers. However, binomial distributions are typically used in experiments where there is a “pass” or “fail” criterial. These will likely not be used in a system-level analysis of a PV plant and are more appropriate to use say in a manufacturing setting when analyzing defective parts used to build a specific component.

8. EXPONENTIAL

An exponential distribution is used for components that have a constant failure rate. Electronic equipment is one area that can be modeled using an exponential distribution. For solar, inverters may have failure modes that follow an exponential distribution.

In this case, we are only considering a one-parameter exponential distribution. As Lambda increases, the distribution moves left and the peak increases (Figure A-8). The inverse of Lambda is the component’s mean time between failure. However, that is only true if the component has a constant failure rate (it cannot be decreasing or increasing over time).
An exponential distribution is also the same as a Weibull distribution when the Beta/slope (shape) is equal to 1, meaning there is a constant failure rate.

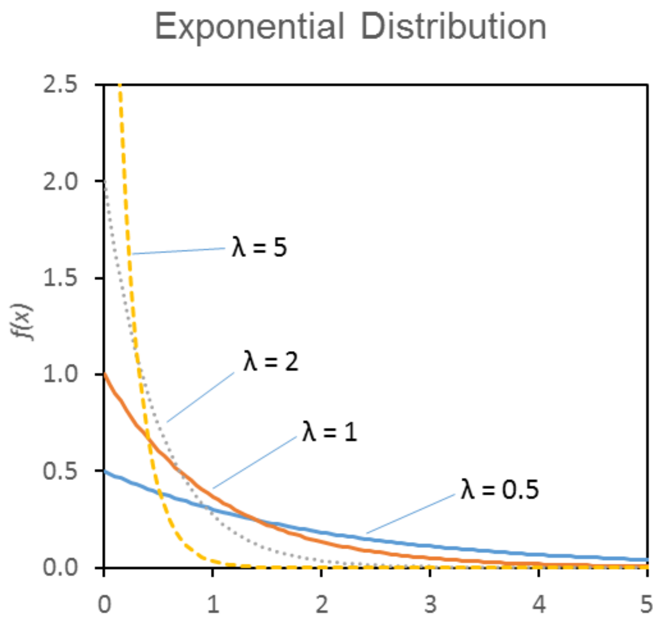

Figure A-8. Exponential Distribution: Change in Lambda

9. WEIBULL

Weibull distributions are the most versatile of all probability distributions and can be used in place of many of the other distributions presented in this appendix as it can handle constant and non-constant (decreasing or increasing) failure rates. It can be used to model component fatigue, corrosion, diffusion, abrasion and other degradation processes.

The Weibull distribution is changed primarily through the shape (slope) and scale (spread) parameters. There are many different parameter labels used in software programs. Therefore, remembering the shape and the scale will translate across different greek symbols used by different authors. The most important aspects of the Weibull distribution are as follows:

- A shape parameter less than 1 means that there is a decreasing failure rate for that component.
    - This can indicate the infant mortality phase where most of the failures have already occurred and become less frequent over time.
- A shape parameter equal to one means the component has a constant failure rate.
- A shape parameter greater than 1 means there is an increasing failure rate.
    - As the component ages, the failure rate may start increasing as it reaches the end of its life.
- The scale parameter helps define the spread of the data and is the 63.2 percentile of the failure data.
    - For the first plot in blue (Shape = 0.5, Scale = 5), (Figure A-9) the scale of 5 would mean that 63.2 percent of the component would fail in the first 2 years (years on x-axis).

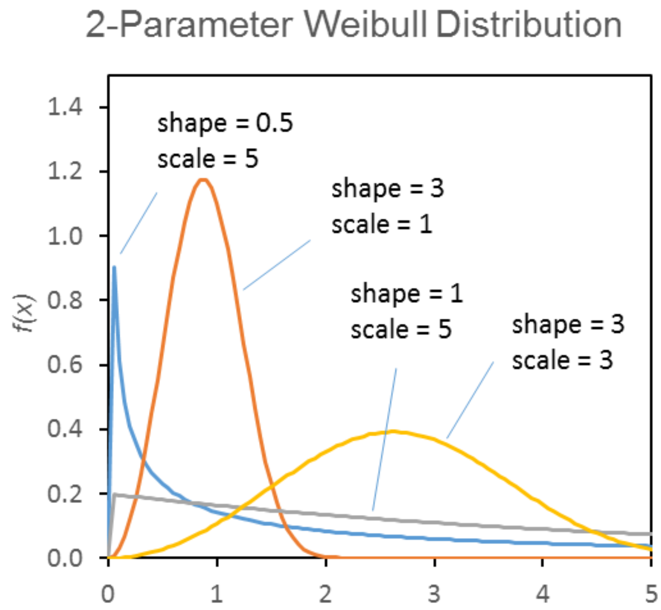

Figure A-9. Weibull Distribution: Change in Shape and Scale

The quintessential bathtub curve that is shown in many discussions of reliability engineering can be constructed from three different Weibull distributions.[6] If, for example, you want to simulate an inverter failure and have some knowledge that the inverter has not yet been extensively field tested. Figure A-10 shows three different distributions that can be used to simulate either general inverter failures, or can be used to isolate a specific component.

Specific repair distributions can also be defined for each failure mode, with parameters chosen to replicate how fast the repair will be addressed depending on the severity of the modeled component, or stage in the component lifetime.

As Weibull distributions are like others presented here, being able to compare different distributions may be of interest. A good way to make this comparison is available in this on-line calculator.[7]

[6] http://www.weibull.com/hotwire/issue14/relbasics14.htm
[7] http://biodevices.et.tudelft.nl/ReliabilityEngineering/Distributions/Compare/

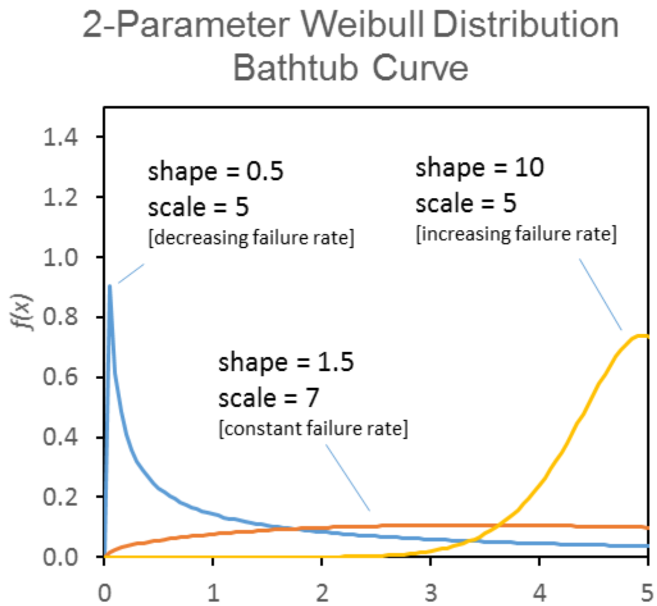

Figure A-10. Three distributions used to develop bathtub curve in a probability plot

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