Evaluating Energy Impacts and Costs from PV Component Failures

Preprint

Janine Freeman,[1] Geoffrey T. Klise,[2] Andy Walker,[1] and Olga Lavrova[2]

[1] National Renewable Energy Laboratory
[2] Sandia National Laboratories

Presented at the World Conference on
Photovoltaic Energy Conversion (WCPEC-7)
Waikoloa, Hawaii
June 10–15, 2018

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Technical Report
NREL/CP-6A20-72212
November 2018

Evaluating Energy Impacts and Costs from PV Component Failures

Preprint

Janine Freeman,[1] Geoffrey T. Klise,[2] Andy Walker,[1] and Olga Lavrova[2]

[1] *National Renewable Energy Laboratory*
[2] *Sandia National Laboratories*

Suggested Citation
Freeman, Janine, Geoffrey T. Klise, Andy Walker, and Olga Labrova. 2018. *Evaluating Energy Impacts and Costs from PV Component Failures: Preprint.* Golden, CO: National Renewable Energy Laboratory. NREL/CP-6A20-72212. https://www.nrel.gov/docs/fy19osti/72212.pdf.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Technical Report
NREL/CP-6A20-72212
November 2018

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

Evaluating Energy Impacts and Costs from PV Component Failures

Janine M. Freeman[1], Geoffrey T. Klise[2], Andy Walker[1], Olga Lavrova[2]

[1]National Renewable Energy Laboratory, Golden, CO, 80401, USA
[2]Sandia National Laboratories, Albuquerque, NM, 87185, USA

***Abstract* — The PV Reliability Performance Model (PV-RPM) tool is used to simulate the cost and energy impacts of component faults and failures for a hypothetical PV system. This model, originally developed by Sandia National Laboratories, is a new feature in the National Renewable Energy Laboratory's System Advisor Model (SAM), which performs stochastic analysis sampling of probability distributions for faults, failures, and repairs. One PV system was created for this analysis to be representative of a portfolio of maintenance data maintained by Sandia National Laboratories. Fault, failure, and repair distributions from this system are varied from current baseline conditions to simulate different reliability and repair scenarios and resulting energy and cost impacts. Results highlight ways to express the uncertainty around PV system performance when considering the probabilistic behavior of components in the system, and ways the PV-RPM model can be used to explore different failure and repair scenarios.**

I. Introduction

Sandia National Laboratories (SNL) has been collecting maintenance data from operational PV systems to work with industry partners to better understand and characterize how component events are impacting system performance [1]. SNL worked with the National Renewable Energy Laboratory (NREL) using the SNL reliability dataset in the development of O&M cost budgets for new PV systems in the PV O&M Cost Model [2], and in the PV Reliability Performance Model (PV-RPM) in the System Advisor Model (SAM) to perform probabilistic simulations of lifetime performance based on fault and failure distributions [3,4,5]. These tools allow for many different types of planning scenarios for new or existing PV systems, considering different component failure rates and maintenance scheduling scenarios, and modeled scenarios, using an existing system's fault/failure and repair distributions to evaluate the uncertainty in energy production based on how the system is currently performing. The PV-RPM tool allows one to analyze not only the reduction in power due to a failed component, but also the cost to repair the component, which are then used as inputs in a SAM simulation so that the effect of both the reduced power and the repair cost are included in the calculated levelized cost of energy (LCOE).

We used the PV-RPM tool to conduct hypothetical reliability scenario analysis utilizing existing fault/failure and repair distributions from the SNL reliability dataset for a fictitious 305 kW_{DC} system. This system is meant to represent a system within Portfolio D, which consists exclusively of distributed generation (DG) as compared to other data portfolios managed by SNL (Table 1). We use this system to establish a baseline in terms of estimated performance (energy, O&M costs, and LCOE) considering a selection of existing failure and repair rates. We then vary fault and failure distributions and different repair scenarios to compare to the baseline scenario.

II. Portfolio and Dataset

The SNL portfolio has a total capacity of 780 MW_{DC} with a total of 144 systems. Currently, 56% (109 out of the 189 PV systems) have maintenance data recorded against specific components. This represents around 510 MW_{DC} out of the total 780 MW_{DC} in the portfolio. The data collection range varies for each portfolio as shown in Table I.

Fig. 1 presents the total number of both faults and failures collected by SNL within all portfolios. The data is sorted by the component with the most events in the database, to those that have the fewest catalogued events.

TABLE I
Current Portfolio Summary

Portfolio	Comm. year	Data collection range	# of systems	MW_{DC}	% DG	% utility scale
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*

Comm. – commissioning

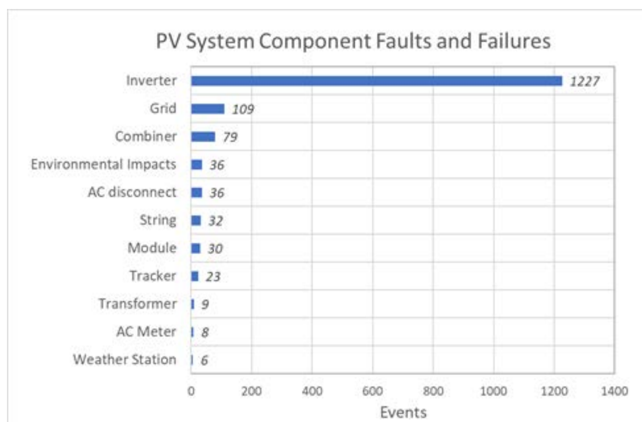

Fig. 1. Summary of number of events (faults and failures) across all portfolios

The 305 kW_{DC} system used in this analysis is representative of Portfolio D, which is characterized in Fig. 2 as a function of the percentage of events (both faults and failures) that cover the data collection timeframe of 2013 to 2017. An "event" is any fault or failure that triggers a trouble ticket in the computerized maintenance management software. Inverters make up about half of all events within Portfolio D, followed by grid issues (external to the PV system). Combiner issues are next, then followed by environmental impacts, AC meter, string and finally weather station outages.

Previous work [1] analyzed the failure information in these datasets to fit statistical distributions to the failure and repair times of components in these datasets.

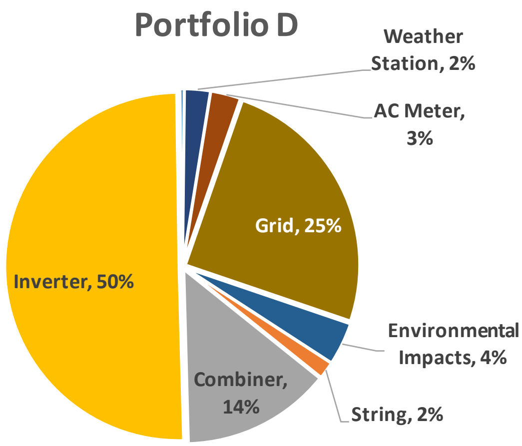

Fig. 2. Component event percentages for Portfolio D

III. Baseline Scenario

To conduct the analysis at hand, we first established a baseline scenario, representing current reliability and repair information, for comparison against our hypothetical reliability scenarios. In SAM, we created a fictitious system design representing a 305 kW_{DC} ground mount system from Portfolio D of the maintenance data. We populated this simulation with system cost data corresponding to a commercial system in the "U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017", with a total installed cost of \$1.84/W_{DC} and an assumed inverter replacement at 10¢/W_{DC} in year 15 [6]. For the financial model, we used the Single Owner model within SAM, using mostly its default inputs, and examining the system over a 20-year lifetime. [1]

We then set up a stochastic component reliability analysis in the PV-RPM tool within SAM to run on our representative PV system. We modeled failures for *only* the top three components with the most failures from Fig. 2: inverters, DC combiners, and the grid. All other components were assumed *not to fail*, which will artificially lower final LCOEs. For each component, we selected representative failure distributions and their corresponding repair distributions from Appendix A of [1]. Three common failure modes were selected for the inverters: fan failures, power cycling failures, and insulated gate bipolar transistor (IGBT) failures. Only two failure modes were available for the grid and one for DC combiners, so all of those failure distributions were used for their respective components. Table II shows the selected failure and repair distributions for each component. Note that although sub-components are replaced, none of these failure distributions model the end-of-life failure and total replacement of the entire inverter, so the assumed total inverter replacement in year 15 remained in our simulation, consistent with the inverter lifetime estimate used in [6].

Finally, repair costs, repair labor time, and labor rates for each failure type were taken from the spreadsheet O&M cost model associated with [7] and entered into the PV-RPM tool within SAM. These costs and repair times are shown with their corresponding failure mode in Table II.

With our baseline scenario completed with a system design, system costs, representative failure and repair distributions, and associated repair cost information, we ran 50 stochastic realizations of this hypothetical scenario to establish our baseline LCOE range.

In addition to our baseline scenario, we ran the baseline system in a deterministic manner assuming no component failures whatsoever throughout the lifetime of the system. This demonstrates the lower limit for the improvement that our assumed reliability and repair scenarios can provide. Assuming a 20-year system lifetime, the no-failure LCOE of this system is 9.50¢/kWh.

IV. Reliability and Repair Scenarios

After establishing our baseline scenario, we simulated several different reliability and repair scenarios. These scenarios fall into three different categories: 1) improved reliability scenarios, where we extend the time to failure as a proxy for improved component reliability, 2) improved repair scenarios, where we shorten the time to repair, and 3) an improved inverter lifetime scenario, where we lengthen the assumed lifetime of the inverter, versus improving reliability of the non-fatal failure modes we chose to model.

For the improved reliability scenarios, we first explored an "attainable" improvement where it takes components 20% longer to fail. We accomplished this, after sampling the original failure distributions, by multiplying the sampled failure time for each component by 1.2 (applied evenly across all failure modes), thereby shifting the entire sample set 20% to the right. We did this for each component type individually, leaving the other components using their baseline failure distributions, as well as for all three components simultaneously, to allow us to explore the relative impact of different component failures. We also explored a more ambitious reliability improvement, where we doubled the time it took components to fail, again for each component individually and then for all three simultaneously.

For the improved repair scenarios, we performed a similar shift, but in the opposite direction. We explored a regime where time to repair is cut in half by multiplying each sampled repair time by 0.5. This could represent some combination of faster failure identification and shorter lead times on repairs.

[1] The SAM file and PV-RPM scripts used for this analysis will be posted on the SAM website at https://sam.nrel.gov/pvrpm

TABLE II

FAILURE AND REPAIR DISTRIBUTIONS AND ASSOCIATED COSTS

Failure Mode	Failure Distribution	Repair Distribution	Repair	Labor Hrs	Material Cost	Total Cost
DC Combiner Failure: Unknown Cause	Weibull Shape: 0.51 Scale: 1200000	Lognormal-n Mean: -0.98 Std: 2.07	Replace MC connector lead to combiner	0.1	$20	$22.40
Inverter Failure: Fans	Weibull Shape: 12.34901 Scale: 273.5486	Lognormal Mean: 3.86093 Std: 11.9357	Replace inverter fan motor	1	$120	$144.04
Inverter Failure: Power Cycling	Weibull Shape: 3.09197 Scale: 418.1346	Lognormal Mean: 4.73865 Std: 4.41415	Reboot for unknown error	0.25	$0	$6.01
Inverter Failure: IGBT Matrix	Weibull Shape: 111.0869 Scale: 1693.973	Lognormal Mean: 1.5026 Std: 2.17808	Replace IGBT matrix	4	$20,000	$20,096.16
Grid Failure: Unknown	Lognormal-n Mean: 3.62 Std: 1.7	Weibull Shape: 1.07 Scale: 0.16	Utility side	0	$0	$0.00
Grid Failure: Recloser Trip	Weibull Shape: 1.36296 Scale: 332.93	Lognormal-n Mean: -1.72747 Std: 1.16951	Utility side	0	$0	$0.00

For the improved inverter lifetime scenario, we ran the baseline scenario, with all its component and repair distributions exactly the same as before, except we removed the cost of replacing the inverter in year 15. This assumes that the smaller, non-fatal inverter sub-component failures still occur throughout the system lifetime, but the fatal failure of the entire inverter requiring full replacement is pushed past the end of the assumed system lifetime, in this case 20 years. This allows us to compare the effect of improving inverter lifetime to improving the occurrence of the three non-fatal failures that we examined for inverters (fans, power cycling, and IGBT).

In total, we ran 12 different reliability and repair combinations and 1 inverter lifetime scenario stochastically in PV-RPM in SAM, with 50 stochastic realizations for each reliability/repair scenario. The PV-RPM model in SAM calculates a variety of output statistics [4], but in this analysis we will focus on the LCOE of the system, documented in [8], since this metric accounts for both system performance and system costs. We present the average LCOE for each batch of stochastic simulations as the main metric, but because the simulations are stochastic, we also provide some information on the range of LCOEs calculated across those 50 simulations. In this analysis, we use the 90th and 10th percentiles to illustrate the range of stochastic results. We determine each percentile empirically by sorting the LCOE results of all 50 simulations and choosing the points corresponding to the desired percentile. Together, these percentiles show the LCOE range containing 80% of the simulations.

IV. ANALYSIS & RESULTS

Fig. 3 presents a summary of the reliability and repair scenarios we examined. The average LCOE and 90th and 10th percentile LCOEs for the baseline scenario are plotted as dash-dot lines, labelled on the right. The purple diamonds show the average LCOE of the scenarios where time to failure is increased by 20%, the green circles show the average LCOE of the scenarios where time to failure is doubled, and the blue circles show the average LCOE of the scenarios where time to repair is cut in half. The different series are grouped together along the x-axis according to which component distribution was varied from the baseline in that simulation: the DC combiner only, the inverter only, the grid only, or all three components combined. The error bars around each point show the 10th percentile of the stochastic simulations on the lower end and the 90th percentile of the stochastic simulations on the upper end. The dashed lines toward the bottom of the plot, labelled on the left side, show 1) the average LCOE of the 50 simulations where the baseline scenario was run without any inverter replacement costs, and 2) the LCOE of the baseline system with no component failures whatsoever.

As one can see in Fig. 3, varying the failure or repair times for the DC combiners yields almost no improvement compared to the baseline scenario. This is an expected result: since we assumed two strings per combiner in our system, a failed DC combiner has the smallest effect on the power production of the system, versus an inverter or the grid which prevents power delivery from a much larger portion of the system. As you can see from Table II, the cost of repairing this DC combiner failure is also fairly low, so that the repair costs likewise have a small impact on LCOE.

Failures of the grid, on the other hand, prevent power delivery from the entire system. Even though they have a large effect when they are happening, the grid failure and repair scenarios only move the LCOE by a maximum of 0.05 ¢/kWh in this hypothetical scenario.

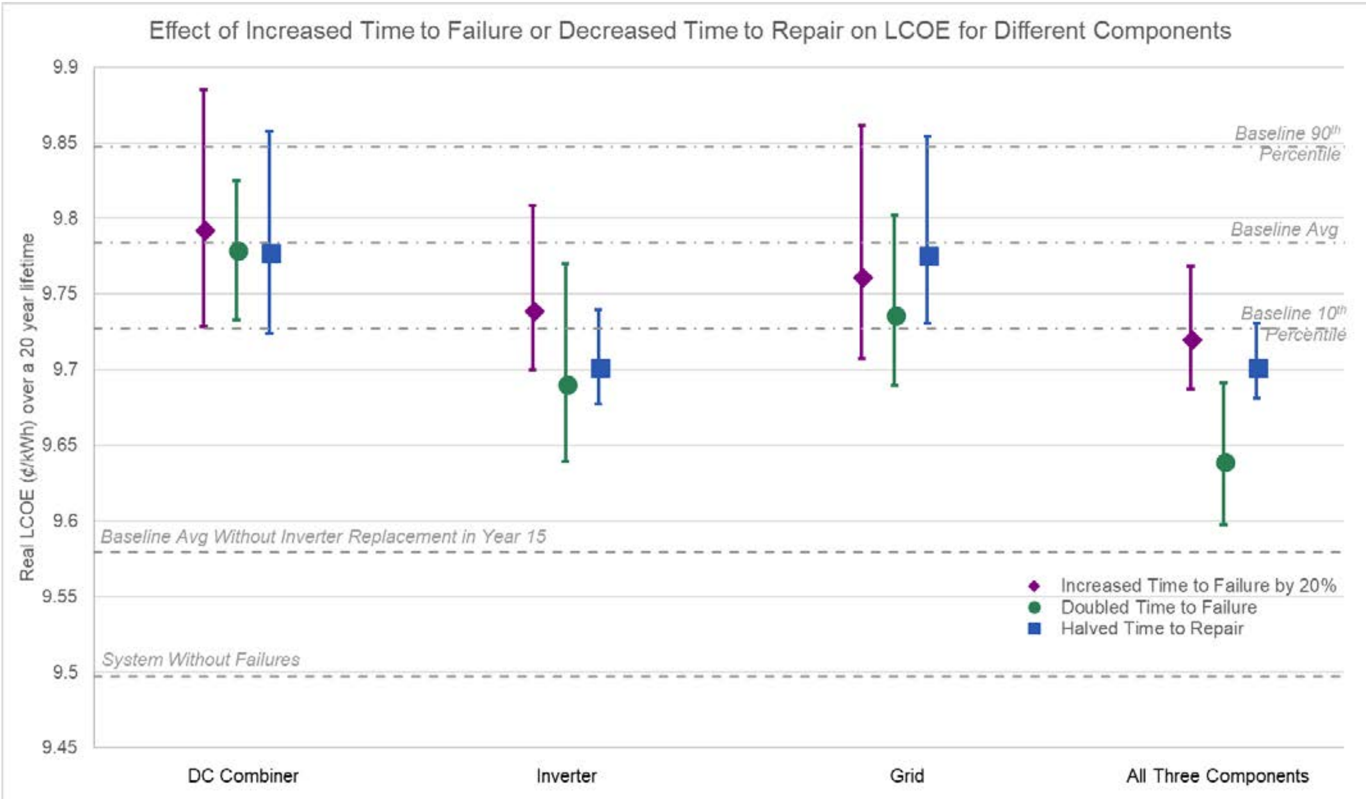

Fig. 3. Effect on LCOE of increased time to failure or decreased time to repair for the DC combiner, Inverter, Grid, or all three components combined, with baseline scenario lines for reference

This results jointly from the facts that 1) grid failures do not cost the system operator anything to fix, so reducing the number of grid failures doesn't affect LCOE from a repair costs perspective, and 2) although grid failures are one of the top three most frequent failure types, their base repair distributions from representative systems in Portfolio D indicate that they are not of a very long duration, so they do not have a large effect on the power production of the system. The latter conclusion is further supported by the fact that reducing grid repair time has a smaller effect than reducing the number of grid failures.

The inverter reliability and repair scenarios have the largest effect of any single component on the system, showing average LCOE reductions ranging from 0.04 - 0.09 ¢/kWh in this hypothetical scenario. Interestingly, for this component, shortening repair time by 50% has a larger effect than increasing time to failure by 20%, and almost as large of an effect as doubling time to failure. However, despite the fact that the average number of inverter failures is halved in the doubled-time-to-failure scenario (decreasing from 28 to 14 failures over the lifetime), this scenario still represents only about a 1% reduction in LCOE for this combination of failure modes. This is partially due to the fact that the IGBT failure- the most expensive to fix- was rarely triggered in these scenarios due to the formulation of the PV-RPM model; only the earliest failure mode occurs (in this case, either the fan or power cycling failure), then all failure modes are re-sampled. *Future work allowing multiple failure modes to occur in the model before all are reset could lead to very different results.* However, in this hypothetical scenario, even eliminating all failures from the system only results in an LCOE reduction of 0.28 ¢/kWh, or ~3%. So, doubling the time to failure for inverters alone bridges about 1/3 of the gap in LCOE attributable to component failures in this scenario.

As expected, applying the improved reliability and repair scenarios to all three components has a larger effect on LCOE than applying them only to a single component. However, Fig. 3 demonstrates that it is not a purely additive effect; this is expected because of where the failures occur in time, and the fact that the ability of the upstream components to deliver power is still dependent on the operational state of the downstream components. For example, if a DC combiner is operational, but the grid is not, it negates the operational state of the DC combiner, not allowing that improved reliability to pass through to LCOE.

A very interesting result is that in this scenario, simply improving the lifetime of the inverter so that it does not need to be fully replaced during the lifetime of the system has a bigger effect than doubling the time to failure for all the non-fatal component failures considered here, and almost as large of an effect as removing all component failures for this system. This suggests a continued need for research to improve total inverter lifetime, along with some examination of the interaction that these non-fatal failures have with that total lifetime.

Again, these numbers, and the LCOE gap, are specific to this analysis and could change if one considered additional or different components or failure/repair distributions. This points strongly to the need for more comprehensive failure data collection, to help the industry better understand actual failure distributions for a larger collection of systems and failure modes. However, a total possible LCOE reduction of 0.28 ¢/kWh in this scenario is within reason- the U.S. Department of Energy's SunShot 2030 Goals aim for a 0.7 ¢/kWh reduction in LCOE due to lowered O&M costs considering all failure modes for all components, not just these six failure modes for three components [9]. Further research into component reliability will allow industry to identify the best paths forward to achieve the full 0.7 ¢/kWh LCOE reduction via O&M costs.

IV. Conclusions

This paper demonstrates an example of the type of analysis that one can conduct using the PV-RPM model in SAM. Consistent with current industry experience, improvements in inverter non-fatal failures has the largest effect on LCOE of the three components that were examined here (DC combiners, inverters, and the grid) using the distributions identified in this analysis. However, improving the overall inverter lifetime to last beyond the LCOE analysis period had a larger effect than improved reliability or repair times for any component, or all three components combined, pointing to the need for further research and development on inverter lifetime reliability.

The overall improvement to LCOE achieved by any of the examined reliability or repair distributions was fairly small in this hypothetical analysis (about 1%), but this is to be expected given that the total possible reduction in LCOE by eliminating *all* system failures is only 3% in this analysis. This is not entirely inconsistent with other literature on the subject [9], but is nonetheless specific to this analysis. Assuming different failure/repair distributions or repair costs, modeling more system component failures, or modifying the PV-RPM model to better represent partial failures has the potential to change these results dramatically. This indicates that further data collection and analysis on system and component reliability is needed to achieve SunShot O&M cost reduction goals in O&M. Future work should explore different combinations of failure and repair distributions, more components, and possible improvements to PV-RPM in SAM.

System operators can utilize the new PV-RPM feature in SAM using their own datasets to develop and analyze O&M scenarios, and adjust component event probabilities based on assumed or known behavior. Models can provide data-driven support for O&M cost reduction strategies and can be adjusted to account for changes in reliability.

Acknowledgement

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 provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. 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 U.S. Government purposes.

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

References

[1] G. Klise, O. Lavrova, and R. Gooding, "PV Component Fault and Failure Compilation and Analysis." 2018 unpublished report, Sandia National Laboratories, Albuquerque, NM.

[2] SunSpec Alliance, "PV O&M Cost Model user guide, draft v0.9", 2017. Available at: https://sunspec.org/wp-content/uploads/2016/03/SunSpecPVOMCostModelUserManual-Beta.pdf. For an on-line version of cost model, see apsuite.sunspec.org

[3] G. Klise, O. Lavrova, and J. Freeman, "Validation of PV-RPM Code in the System Advisor Model," SAND2017-3676, Sandia National Laboratories, Albuquerque, NM, April 2.

[4] G. Klise, J. Freeman, O. Lavrova, and R. Gooding, "PV-RPM v2.0 beta – SAM Implementation Beta Test: User Instructions." June 2017.

[5] PV-Reliability Performance Model – System Advisor Model. Available at: https://sam.nrel.gov/pvrpm

[6] R. Fu, D. Feldman, R. Margolis, M. Woodhouse, and K. Ardani, "U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017", NREL/TP-6A20-68925, National Renewable Energy Laboratory, Golden, CO, September 2017.

[7] NREL/Sandia/SunSpec Alliance SuNLaMP PV O&M Working Group, "Best Practices in Photovoltaic System Operations and Maintenance, 2nd Edition", NREL/TP-7A40-67553, National Renewable Energy Laboratory, Golden, CO, December 2016.

[8] System Advisor Model Version 2015.9.7 User Documentation, Levelized cost. National Renewable Energy Laboratory, Golden CO, 2017.

[9] U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office, "SunShot 2030 Fact Sheet", DOE/EE-1501, August 2017.