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Analytical Improvements in PV Degradation Rate Determination

Dirk Jordan and Sarah Kurtz

Presented at the 35th IEEE Photovoltaic Specialists Conference (PVSC '10)
Honolulu, Hawaii
June 20-25, 2010

Conference Paper
NREL/CP-5200-47596
February 2011

Contract No. DE-AC36-08GO28308

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ANALYTICAL IMPROVEMENTS IN PV DEGRADATION RATE DETERMINATION

D.C. Jordan, S.R. Kurtz
National Renewable Energy Laboratory, Golden, CO 80401, USA

ABSTRACT

As photovoltaic (PV) penetration of the power grid increases, it becomes vital to know how decreased power output may affect cost over time. In order to predict power delivery, the decline or degradation rates must be determined accurately. For non-spectrally corrected data several complete seasonal cycles (typically 3-5 years) are required to obtain reasonably accurate degradation rates. In a rapidly evolving industry such a time span is often unacceptable and the need exists to determine degradation rates accurately in a shorter period of time. Occurrence of outliers and data shifts are two examples of analytical problems leading to greater uncertainty and therefore to longer observation times. In this paper we compare three methodologies of data analysis for robustness in the presence of outliers, data shifts and shorter measurement time periods.

INTRODUCTION

In this paper we will focus on determining degradation rates from continuous data. For non-spectrally corrected measurements, particularly using pyranometers, it is well known that due to seasonal changes, several complete cycles (typically 3-5 years) need to be completed to obtain reasonably accurate degradation rates [1]. The first step in determining degradation rates is to translate the parameter of interest to some reference condition. In this paper we have adopted the Photovoltaics for Utility Scale Applications (PVUSA) methodology for ease of use in which case the parameter of interest is the maximum power and the pre-determined conditions are PVUSA Test Conditions (PTC) [2-4]. Once the power has been adjusted to the same condition the data, divided into monthly intervals are charted in sequential order. A linear regression is fitted to this time series using the standard least square method. Considerable attention has been devoted to the first, the translation or normalization step [5-11]. The second step has received less attention and we will focus on it for the remainder of this paper. We will refer to the use of a linear fit to the adjusted data as the traditional method and it represents the first analytical methodology we investigated. The second method is commonly known as the classical decomposition where the signal is parsed into trend, seasonality and remaining irregular component [12]. The last method examined in this study is the *Autoregressive Integrated Moving Average* (ARIMA) modeling approach first introduced by Box and Jenkins in 1970 [13]. This approach is commonly utilized in econometrics to seasonally adjust econometric parameters [14]. ARIMA methods have been successfully used to model solar radiation data [15] and in grid-connected PV power production [16,17].

To test these three different analytical methods, data from the NREL Outdoor test facility were used, deliberately modified as detailed below to test them with respect to outliers, data shifts and reduction of observation time.

MODELING AND ANALYSIS

Classical decomposition, as shown in Fig. 1 separates the total signal into trend, seasonality and remaining irregular component. The trend, Fig. 1 (b) was obtained from the original data with a centered 12-month moving average. The seasonality component is obtained by subtracting the trend from the original data and averaging each month across the years of observation. This is the equivalent of calculating a seasonal index with the assumption that the index does not change across the time of observation. After the seasonality component is known, and using the trend data, the irregular remaining component can be calculated. Degradation rates using the classical decomposition are determined from the trend graph of Fig. 1 (b) in contrast to the traditional method, which uses Fig. 1 (a). The marked hump in the trend graph is a data shift caused by a maintenance event and will be addressed later.

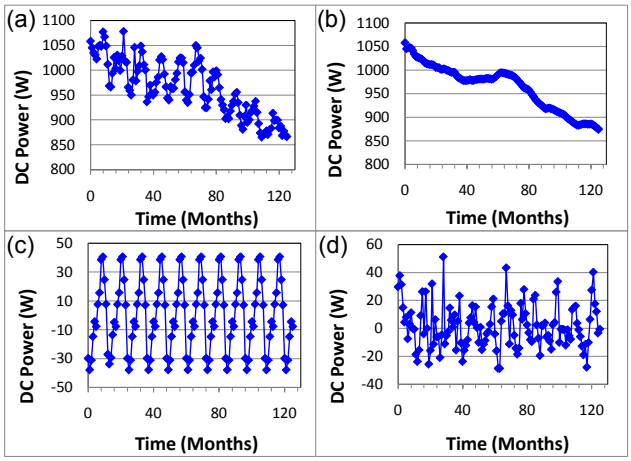

Figure 1 Classical time series decomposition. The data set for an a-Si module (a) is shown along with its components of (b) trend, (c) seasonality and (d) remaining irregularity.

To facilitate the understanding of the ARIMA modeling it is helpful to consider PV degradation rates in a more

mathematical context. Degradation rates, i.e. the change of power with time, is proportional to the power and a random error term, as stated in Eqn. 1, where c is a constant and ε a random fluctuation term.

$$\frac{dP}{dt} = c + P + \varepsilon \quad (1)$$

However, the power change is not observed in infinitesimally small intervals but very large time intervals, as shown in Fig. 1. Therefore, the stochastic differential equation (1) becomes a stochastic difference equation. It can be shown in some simple algebraic steps that Eqn. 2 follows, where δ is a constant, ϕ a (fixed) coefficients and ε the random fluctuation at point t.

$$P_t = \phi \cdot P_{t-1} + \delta + \varepsilon_t \quad (2)$$

Equation 2 is called an autoregressive equation since the power at point t is regressed onto its lagged self. This

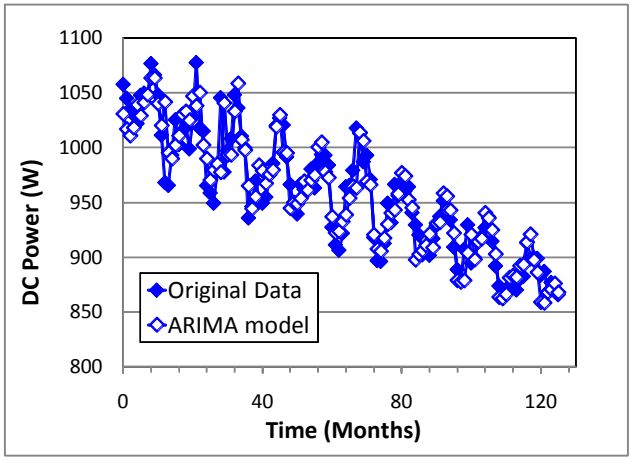

Figure 2 Amorphous Si data set (solid diamonds) and ARIMA modeled data (open diamonds).

autoregressive model is a subset of a much larger class of ARIMA models. An ARIMA model predicts the current value in a time series as a linear combination of past values (the autoregressive part) and past random fluctuations (the moving average part). These models require stationarity of the time series, i.e. the data fluctuate around a constant mean. If a trend is visible, stationarity of a time series can be achieved by taking the difference of subsequent points which is the integrated part of the ARIMA notation. Figure 2 shows an example of an amorphous-Si data set overlaid with an ARIMA model. The actual algebraic representation for the ARIMA model is given in the simple but somewhat cumbersome Eqn. 3, where ϕ and θ are the autoregressive and moving average coefficient, respectively. An abbreviation for Eqn. 3 is given by ARIMA (100)(011) with seasonality period of 12 month. In this notation, the first numeral indicates the autoregressive, the middle numeral indicates the integrated, and the last numeral is the moving average part. Non-seasonal components are specified by the former, seasonal components by the latter bracket.

$$P_t - P_{t-12} - \phi \cdot P_{t-1} + \phi \cdot P_{t-13} = \delta + \varepsilon_t - \theta \cdot \varepsilon_{t-12} \quad (3)$$

OUTLIERS

To test the sensitivity of the different methodologies to outliers, a "clean" data set, was selected. As shown in Fig. 3, one to five outliers were deliberately and subsequently introduced and the degradation rate calculated for each method. Figure 3 (b) shows the result and the impact of the outliers on the degradation rates for the three different methodologies. The uncertainties displayed are statistical uncertainties only, which may differ from the error of the true degradation rate, but allow

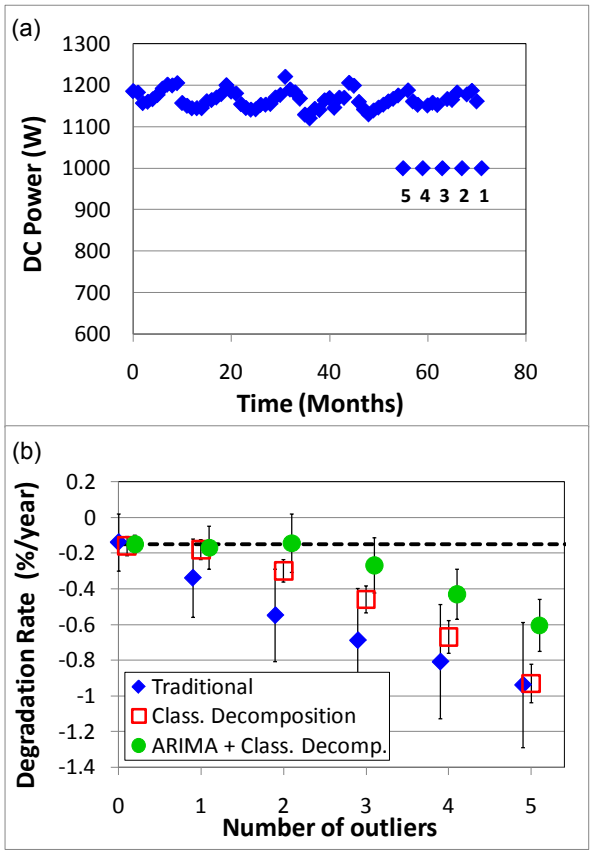

Figure 3 Performance of a multi-crystalline silicon module deployed at NREL (a) with deliberately introduced outliers 1-5 and (b) the resulting degradation rates.

direct model-to-model comparison. For the traditional way, the statistical uncertainties, the Type A uncertainty according to the ISO guide to the Expression of Uncertainty [18], can be calculated directly from the standard errors of the regression. The uncertainty of the

classical decomposition is composed of two components. The first is similar to the traditional way and can be calculated from the standard errors of the regression. Since each data point represents the 12-month average each individual data point contains a second uncertainty component. The variances of the two components are added to obtain the total Type A uncertainty. In ARIMA modeling the main uncertainty originates from the model identification phase where model components are chosen based on a multitude of different mathematical criteria. Therefore, three different models based on the more robust mean absolute deviation were selected to determine the uncertainty. Subsequently, the median rate and standard deviation were calculated. Without any outliers, all three methodologies converge to the same degradation rate within one standard deviation. Using the traditional method, it can be seen that even the occurrence of one outlier shifts the degradation rate and increases the uncertainty significantly. Traditionally, those points most likely would have been discarded to determine the proper degradation rate. Using the classical decomposition, one outlier does not alter the degradation rate but the occurrence of two does. The ARIMA approach is even more robust. At three outliers, the median degradation rate is slightly too high but still within the uncertainty bar. Four or more outliers result in an incorrect degradation rate even with the ARIMA modeling.

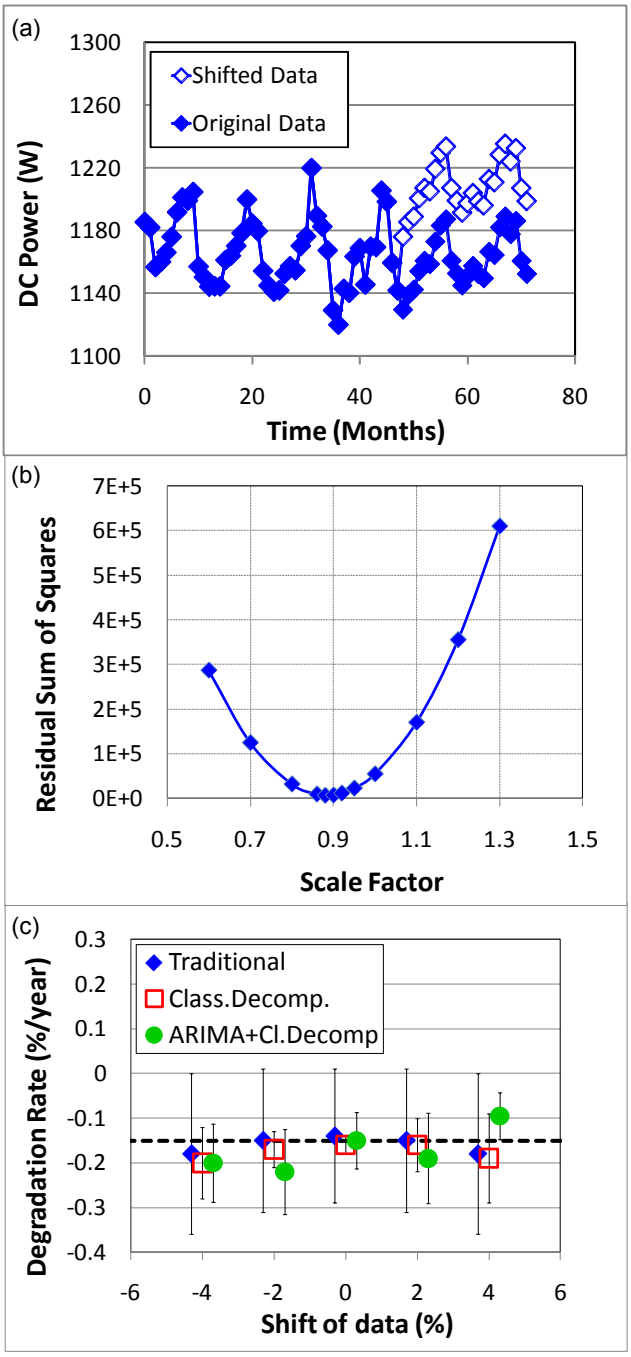

Figure 4 (a) Data shift deliberately introduced in a data set, (b) minimization of residual error to determine best scaling factor, (c) comparison of original with shift-corrected data.

DATA SHIFT

Data shifts, typically associated with hardware changes present an especially difficult problem due to the question of alignment of the individual data blocks. ARIMA methodology excels at modeling weak trends but is seriously limited when sudden changes occur. In this section we demonstrate how data shifts can be corrected without discarding any data and eliminating a stringent limitation of ARIMA modeling. In Fig. 4 (a) the same data

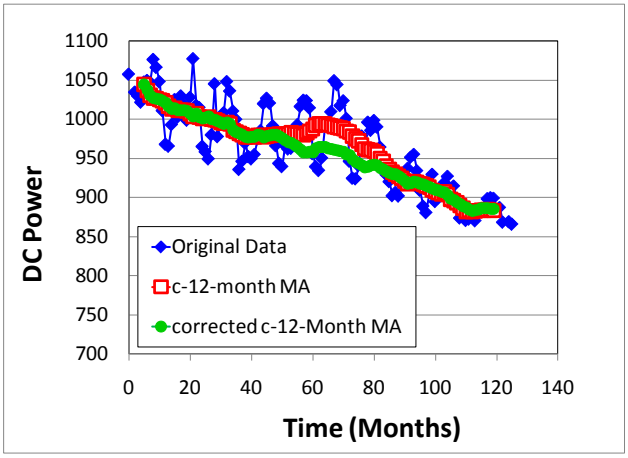

Figure 5 Amorphous Si data from Fig. 1 with shift-corrected trend component. The trend was obtained with a centered 12-month moving average.

from a multi-crystalline Si module, as in the previous section was selected with a shift for a 2-year period deliberately introduced. The shifted data are multiplied then by a scaling factor that, depending on its value, can shift the 2-year window below or above the rest of the data set. For all three approaches the residual sum of squares was plotted as a function of scaling factor similarly to Fig. 4 (b). When the residual sum of squares is minimized the

best fit of the shifted data to the rest of the data is determined. Figure 4 (c) shows that all three approaches lead to the determination of the degradation rate without any shift. This correction methodology was applied to the data set of Fig. 1 with the results shown in Fig. 5. It can be seen that the correction procedure removes the hump in the middle of the data set which was caused by an out-of-calibration temperature sensor. The same methodology can also be used when there is not an abrupt shift but a gradual continuous deviation such as caused by sensor drift. Instead of a single correction factor a correction function can be applied to the original data with residual minimization as described above.

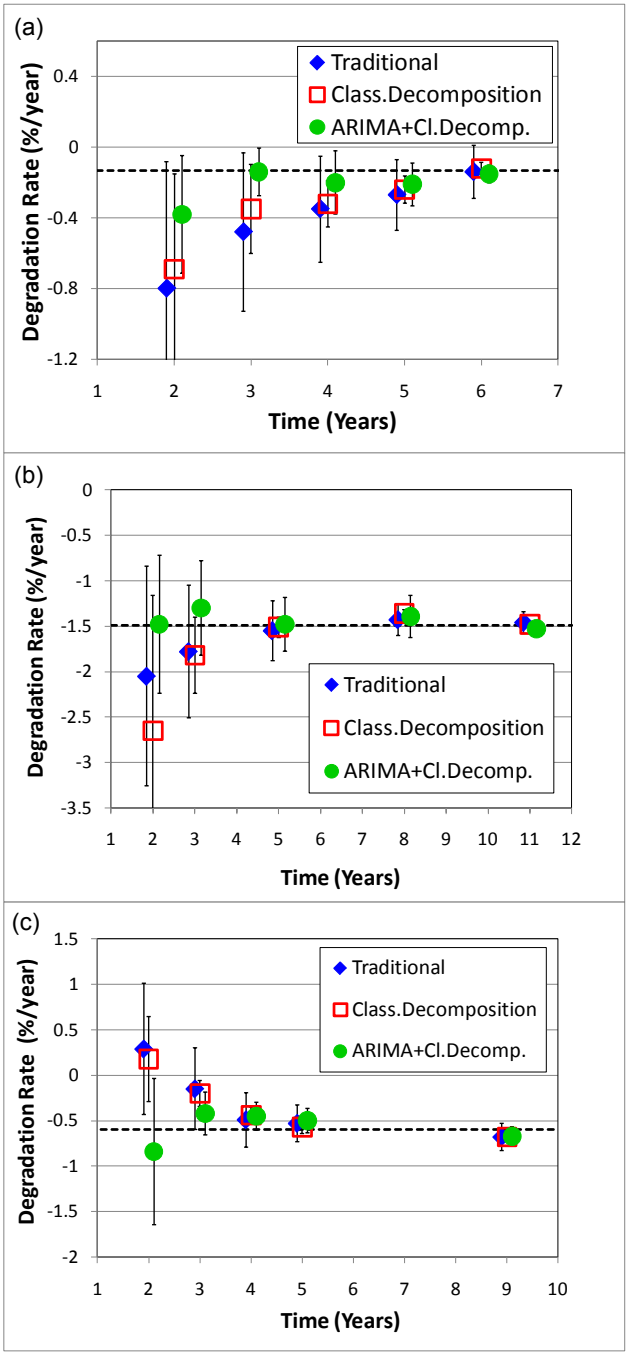

Figure 6 Degradation rates with changing observation time (a) for a multi-crystalline Si, (b) amorphous Si, and (c) thin-film module.

SHORTER OBSERVATION TIME

A natural extension of the above observation that the ARIMA models seem more accurate than the traditional method is to investigate whether degradation rates can be determined in shorter time. For this purpose, in Figure 6 (a) a multi-crystalline Si module, (b) an amorphous Si module, and (c) a thin-film module were chosen. Both the amorphous Si and the thin-film module were exposed in the field prior to the data shown here, thus degradation rates were determined after modules had stabilized. Degradation rates were calculated for each method starting with the first 2 years, 3 years, etc. until all data were used. For simplicity sake we assume a constant degradation rate for the moment. As the number of years of measured data increases all three methodologies converge to the same rate; at shorter time periods, however, differences start to occur. The multi-crystalline Si module, Fig. 6 (a), shows increasing bias at shorter time periods for the traditional and classical decomposition. At two years even the ARIMA shows some bias but it is closer to the long-term degradation rate with smaller uncertainty than the other two methods. More remarkable are the results for the amorphous Si module. The ARIMA approach determines the long-term degradation even in two years while both traditional and classical decomposition show some bias although within the uncertainty bar. Similarly, results for the thin-film module are shown after stabilization in the field. Again the ARIMA approach is close to the long-term degradation rate even at two years whereas the other two methods start to show systematic bias.

An important assumption so far has been that the degradation rate is constant over time and that conditions remain the same across the observation time. However, it has been observed and is well-known that degradation rates, especially in the initial phase, are non-linear [19,20]. The ARIMA modeling approach can still be used but is then composed of two parts, a transfer function that relates the input series (time) to the output series (power) and a model for the residual noise. Since the identification and complexity increases significantly for these models [21] we discuss it in a separate study.

It appears that the ARIMA modeling is a powerful approach to determine degradation rates more efficiently. The efficiency of the ARIMA modeling is based on the number of data points, or number of degrees of freedom, available to construct a model. To obtain degradation rates in shorter time but at the same time retaining a large number of degrees of freedom the only choice is to

decrease the sampling interval, from monthly to weekly, for instance. Figure 7 shows the results for the multi-crystalline data set in weekly intervals in contrast to monthly intervals of Figs. 3 (a) and 6 (a). A lot more outliers are now present than with the monthly series, however we have shown that the ARIMA is more robust against outliers and does determine the ultimate degradation rate in as short of a time period as 1.5 years, Fig. 7 (b)

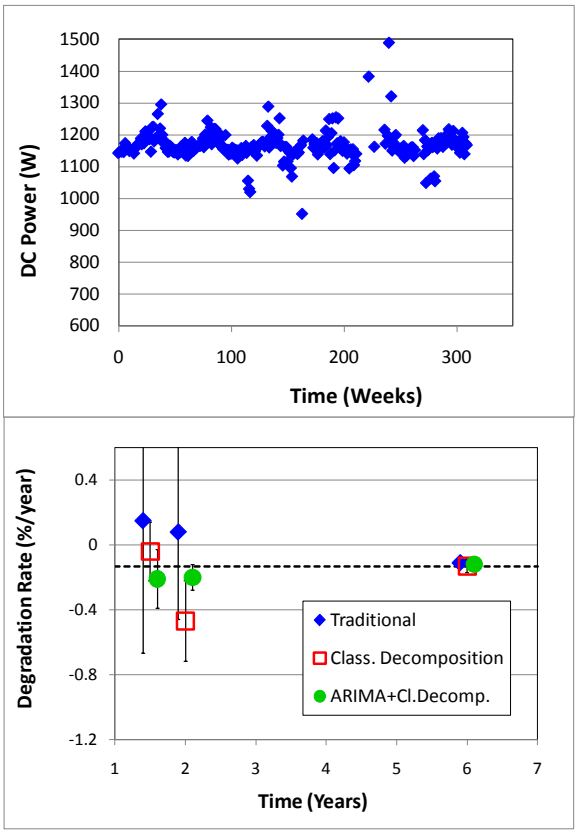

Figure 7 (a) PVUSA regression of a multi-crystalline module in weekly intervals and (b) degradation rates with changing observation time.

CONCLUSION

In summary, we have introduced two alternative analytical ways to determine degradation rates from continuous data, the classical decomposition and ARIMA method. We have shown that these analytical methods have smaller uncertainties than linear fits using standard least squares. Especially the ARIMA method appears to be a robust methodology to a common analytical problem such as outliers. Furthermore, we introduced a method to statistically correct data shifts that are commonly linked to hardware issues. Additionally, we have applied these methods to determine degradation rates more quickly. The ARIMA transfer function approach is ideal to model non-linear behavior and will be the subject of an additional study.

ACKNOWLEDGMENT

We would like to thank Ryan Smith and the rest of NREL's Reliability group for helpful discussions. This work was supported by the U.S. Department of Energy under Contract No. DE-AC36-08-GO28308 with the National Renewable Energy Laboratory.

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4. TITLE AND SUBTITLE
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5a. CONTRACT NUMBER
DE-AC36-08GO28308

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
D.C. Jordan and S.R. Kurtz

5d. PROJECT NUMBER
NREL/CP-5200-47596

5e. TASK NUMBER
PVD9.1310

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
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1617 Cole Blvd.
Golden, CO 80401-3393

8. PERFORMING ORGANIZATION REPORT NUMBER
NREL/CP-5200-47596

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PV degradation

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