Prediction of Acceleration Factor for Accelerated Testing of Photovoltaic Modules Installed Around the World

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Key Words: Photovoltaic (PV) Modules, Acceleration Factor (AF), Accelerated Life Testing (ALT)

SUMMARY & CONCLUSIONS

Acceleration Factor (AF) prediction for accelerated life testing of photovoltaic (PV) modules plays a major role in estimating the reliability of modules in the field. Accelerated stress tests are designed in such a way that the test replicates the failure mechanism that the module experiences outdoor. However, in most cases, both accelerated test degradation data and field degradation data on identical PV modules are not available. In such cases, it is hard to design a test plan and determine the degradation threshold or number of hours (or cycles) required to run the accelerated tests for estimating acceleration factor. This paper presents a novel approach in determining the acceleration factor based on available data from field measurements in different climatic conditions and uses it for determining the acceleration factor for accelerated damp heat (DH) testing of PV modules for 1000 hours (DH1000). Utilizing the available meteorological and degradation data, each field condition is considered as test environment with varying stress levels and a simple linear model is used for predicting the allowed degradation threshold of DH1000 for field equivalent 25 years. Finally, the results are validated from the known accelerated qualification test data and the acceleration factor plot for different regions around the world is presented.

1 INTRODUCTION

Over the last decade, there has been an exponential growth of the photovoltaic (PV) industry, due to lower cost and compelling motivation for conserving fossil fuel energy. This growth was tremendous over the past few years such that the total installed capacity of PV modules has been approaching 200 gigawatts. A typical PV module is expected to have an overall lifetime ranging from 25 to 30 years. Due to rapid evolution of PV technology and relatively young age of PV systems, there is not sufficient data available to study various failure modes occurring in the field. In addition, it is impractical to wait 25 years to study the failure mechanism and measure the actual performance loss to verify the reliability. Therefore, Accelerated Life Testing (ALT) provides a viable way to shorten the test time by using simulated test conditions to replicate the actual field failure modes and mechanisms. But for quantifying the Acceleration Factor (AF), the lack of degradation data in field and limited (or unavailable) degradation data from accelerated qualification test poses a great barrier. Also, in some cases, when there is lack of established standards for accelerated testing of PV modules, then it is of absolute necessity to establish preliminary acceleration factor to design and determine the limit to which the accelerated tests should be done.

An overview of common PV degradation modes and their respective accelerated test procedures, standards and results are summarized in [1, 2]. Usually, the level of power (P_{max}) drop is considered as the qualifying factor for end-of-life determination, ie., when the output power of a module drops below a certain threshold(e.g. 20%) from initial or nameplate data, then the module is considered to be failed. But, extensive field analysis from [2, 3] indicates that the individual parameters like short circuit current (I_{sc}), open circuit voltage (V_{oc}) and fill factor (FF) which dictate maximum power (P_{max}), given in Equation (1), are affected to different degrees depending on the degradation mode(s). By correlating these individual parameters (instead of conventional Pmax) with the individual degradation modes, it is possible to quantify mode-specific degradation rates occurring in the field.

$$P_{max} = I_{sc} * V_{oc} * FF \quad (1)$$

Hence, correlating P_{max} degradation rate to study the impact of specific failure/degradation mode will not be accurate as P_{max} could be potentially affected by a combination of two or more failure modes. Figure 1 provides a detailed flowchart of P_{max} degradation pathway due to the degradation of Isc, Voc and/or FF corresponding to specific degradation mode depending on the site-specific climatic condition. In this study, Interconnect and Metallization System (IMS) degradation is considered. IMS degradation is one of the two most dominant degradation/failure mechanisms that occurs in the field-deployed modules. It has been reported that around 85% of field-deployed modules succumbed to corrosion and cell or interconnect breakage [3]. The effect of IMS degradation can be quantified by observing fill factor or series resistance (R_s) over time. As shown in Figure 1, one or more of the four major failure mechanisms, Intermetallic Compound (IMC) formation, solder bond degradation, corrosion and increase of contact resistance could be responsible for this failure mode. Dynamic stresses due to varying climatic conditions in the field such as higher operating temperatures, day/night or seasonal cyclic temperatures and moisture ingress lead to the occurrence of these failure modes and the changes can be detected by measuring the increase in R_s over time. The R_s increase is related to FF degradation, which in turn causes P_{max} degradation.

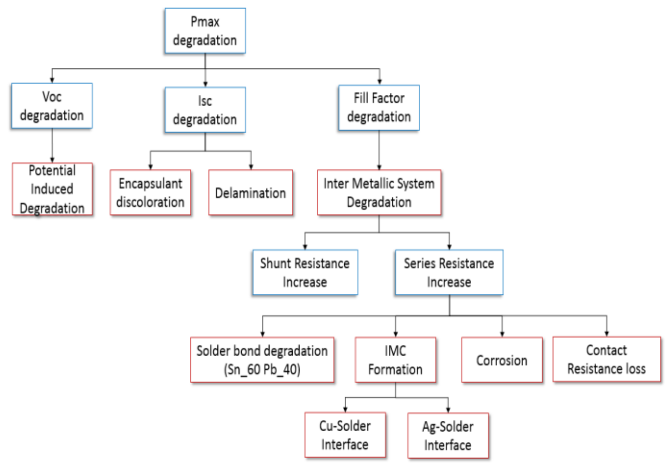

Figure 1: P_{max} degradation flowchart, indicating different components and corresponding degradation parameter

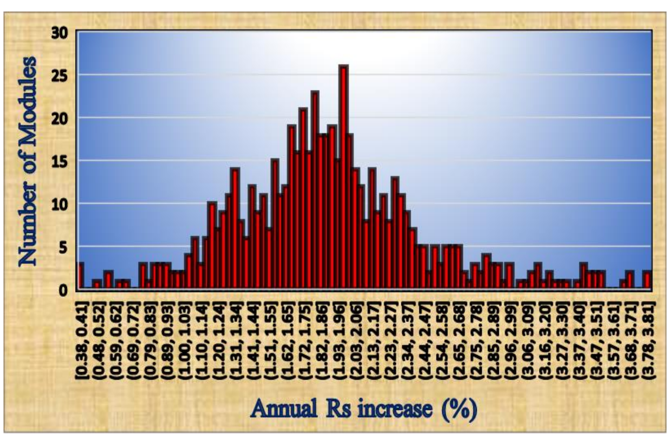

Figure 2: Annual Rs increase (%) for modules installed in Arizona aged 20 years

The qualification testing standard, IEC 61215, specifies the damp heat test for crystalline-silicon PV modules to be exposed to 1000 hours at 85°C temperature (T) and 85% Relative Humidity (RH). Despite the abundance of damp heat test results, there is still a wide range of activation energies reported based on the Pmax degradation for the damp heat test related degradation, thereby limiting the accurate predictive ability of the damp heat model [4]. Also, it is to be noted that a small change in the order of 0.1 eV in activation energy will have a huge impact on the acceleration factor. This paper provides an approach to estimate acceleration factor for global climatic conditions using limited degradation rate available from the field and thereby estimating the degradation threshold for DH1000 beyond which the modules will not survive for the specified warranty of 25 years. The main advantage of this method is that it is simple and can be used to predict acceleration factor for many accelerated life testing methods involving weather parameters. The description of data sources is given in the following subsection.

1.1 Data Description

The hourly meteorological data (TMY3) for different locations is retrieved from EnergyPlus data repository [5]. The DH1000 qualification test database of Photovoltaic Reliability Laboratory (PRL) at ASU [6] contains current-voltage (I-V) data for 135 modules. In addition, the field performance data of about 998 modules aged between 18 to 21 years, deployed in various states like Arizona (3 sites), California (1 site), Colorado (1 site) and New York (2 sites) are also available at PRL. Figure 2 shows the distribution of series resistance increase per year for field aged modules (20 years) deployed in Arizona.

The series resistance values for modules from both DH1000 tests and field test database are calculated using Equation (2) [7].

$$R_s = C_s * \frac{V_{oc} - V_{mp}}{I_{mp}} \tag{2}$$

where, V_{oc} is the open circuit voltage, V_{mp} and I_{mp} are the voltage and current at maximum power point, respectively. The empirical estimate of C_s for poly-crystalline silicon modules is 0.34.

There are many thermal models developed for calculating module temperature, but the NOCT model specified in Equation (3) [8] is accurate and simple as it involves only ambient temperature and global irradiance.

$$T_{mod} = \left(T_{amb} + (NOCT - 20) * \frac{\text{Irradiance}}{800}\right) \tag{3}$$

T_{mod} is the module temperature in degree centigrade, T_{amb} is the ambient temperature in degree centigrade, NOCT value is obtained from California Energy Commission (CEC) database [9], which provides information for around 20,000 modules with different construction types from several manufacturers in the world. The NOCT for polycrystalline silicon modules with glass/polymer construction is distributed normally with mean temperature of 46.5℃ and standard deviation of 1.714℃. The module temperature is converted to the Kelvin scale for model building and analysis. In addition, the module relative humidity is calculated based on model from NREL [10]. There are many parameters involved in the model to get the actual internal module humidity. Some literatures [4] reported using rolling average of ambient humidity but this may not be accurate since the module internal humidity is affected by several factors [10]. Regarding the field data, only the initial nameplate data and final measured data taken after 20 years are available. So, the yearly degradation rate of series resistance is calculated based on the assumption of linear degradation path. Though most modules have been determined to be degrading linearly, still research is being continued in various research organizations to accurately quantify the actual degradation path of PV modules.

2 METHODOLOGY

The construction of PV modules included in this study is glass/backsheet laminates consisting of c-Si cells fabricated from p-type wafers, sandwiched between layers of Ethyl Vinyl Acetate (EVA) encapsulant. In traditional approach, an experiment is conducted (typically at three different temperatures) to estimate the activation energy and then predict the acceleration factor for various field conditions using physics based or data driven approaches. Kimball et al [4] modeled the experimental time to failure by using the data collected for DH1000 with temperatures ranging from 75°C to 95°C and RH varying from 75% to 95%. However, in most cases, the DH1000 qualification tests are done according to IEC 61215 specified at one level of temperature and one level relative humidity (85°C and 85% RH). Hence, it is not possible to calculate activation energy for data collected at a single level of temperature since a minimum of two levels of temperature is needed for estimating the activation energy. So, an alternative approach is developed by using the known/measured values of field degradation rates in different field conditions with identical module construction type.

As PV modules are exposed to different temperature and humidity levels in Arizona, Colorado, California, and New York, the degradation rate in these fields are not expected to be the same. So, these fields are treated as different testing conditions with the factors being temperature and humidity contributing to the increase of series resistance. Since, the degradation rate in these fields are known/measured, model is fitted by treating series resistance degradation rate as dependent variable and climate factors (temperature and humidity) as independent variables to estimate activation energy. Once the activation energy is known, the acceleration factor for any accelerated test can be easily calculated for any field condition. This method is simple but its usefulness depends on fitting a good model to estimate the activation energy. The model is validated using the known actual degradation rates available from PRL database. One interesting information at hand is the availability of field degradation rate data from different climate zones like Arizona (hot and dry), New York (cold and dry), Colorado (temperate) and California (temperate). Hence, the model should be able to accommodate for most of the locations across the globe. The results of model fitting and parameter estimation are given in the next section.

3 DATA MODELLING AND ESTIMATION

As reported in the literature [4, 11], the Temperature - Humidity model (Peck's model) was attempted first but the effect of temperature dominated the module humidity for series resistance increase. In addition, the adjusted R-squared value did not improve significantly with the addition of RH factor. A linear model with natural log transformation of percentage degradation rate per year [ln(% Rs degradation/year)], and inverse transformation of Temperature (1/T) provides a reasonable fit to the data, confirming that module temperature plays a significant role in series resistance increase in the tested modules from field conditions with little and moderate humidity levels. In these low humidity climatic conditions, only the non-corrosion degradation modes seem to be dominating the series resistance increase. The Peck's model including both temperature and humidity may become important in hot-humid locations or highly aged (beyond 25 years) modules as these modules may be dominated by the corrosion reaction. The prediction model is given in Equation (4).

$$y = b_0 + b_1 x_1 \tag{4}$$

Where,

$$y = \ln(\text{\% Rs increase per year})$$
$$x_1 = 1/T_{mod}$$

The model estimates, summaries and ANOVA are given in Figure 3.

Coefficients	Estimate	Std Error	t-value	p-value
Intercept	18.68	0.91	20.39	0.000034
b1	-6868.2	299.39	-22.94	0.000021

R-Squared	99.25%
Adj R-Squared	99.06%

90% Confidence Interval		
	5%	95%
Intercept	16.73	20.64
b1	-7506.43	-6229.9

ANOVA					
	DF	SS	Mean SS	F-value	p-value
b1	1	2.113	2.113	526.25	0.00002
Residuals	4	0.016	0.004		

Figure 3: Model Estimates for Activation Energy determination for IMS degradation

The linear model in Equation (4) with respect to all the transformations is compared to Arrhenius's equation given in Equations (5) and (6).

$$\text{Rate} = Ae^{\frac{-Ea}{kT}} \tag{5}$$

Taking natural log of Equation (5), the model is,

$$\ln(\text{Rate}) = \ln(A) - \frac{Ea}{kT} \tag{6}$$

Where Ea is the activation energy in eV, k is Boltzmann constant (k= 8.617 x 10^{-5} eV/K), and A is the prefactor constant. The statistical estimations from the data are shown in Figure 3, where the parameter estimate b1 is the estimate of activation energy along with Boltzmann constant. So, b_1 divided by Boltzmann constant gives the value of activation energy to be 0.59 eV. The exponential of intercept (b_0) gives the value of prefactor or frequency factor A. The confidence interval of activation energy estimate is 0.59 ± 0.056 eV. The residual plots do not show any violation but the number of data points are low in order to arrive at a solid conclusion. The model fit seems reasonable with a good adjusted R-squared value, which makes it acceptable for prediction.

4 ACCELERATION FACTOR PREDICTION

Once the activation energy is estimated from the field degradation rate data as described in section 3, the same model can be used to predict the acceleration factors for other field conditions using the available weather data and to find the field equivalent hours for the accelerated damp heat testing. The Acceleration Factor (AF) is defined as the ratio of stress/degradation rate in accelerated test to the stress/degradation rate in the field and is given by Equation (7), where stress rate is defined as the inverse of time-to-failure (TTF).

$$\frac{1}{h}\sum_{t=1}^{h} AF_t = \frac{f(T_{acc})}{f(T_{mod,t})} \quad (7)$$

The stress rate in the numerator is due to the accelerated test chamber temperature (T_{acc}). The denominator is the field stress due to hourly module temperature ($T_{mod,t}$) where 't' is the instantaneous time for a given time period of 1 to 'h'. For DH1000 qualification testing, the value of T_{acc} is 85° C. Substituting all the estimated and collected values in Equation (7) using the model in Equation (4) or (6), the mean acceleration factor is determined for a specific module and a specific climatic condition. Assuming that the daytime maximum temperature of the module is responsible for the series resistance increase, 1000 hours of daytime maximum temperature is used for this study. Also, the effect of module internal humidity may also play a role but the temperature effect is expected to be much dominant in our field test conditions as no visible metallic corrosion was observed in those field measured modules. In addition, a simple and efficient module humidity model could be used if the user intends to study its effect. Figure 4 shows the acceleration factor plot for different regions using the estimated activation energy. Figure 5 shows the maximum allowable Rs degradation (%) for the modules during DH1000 testing in order to survive 25 years in the field. For instance, if the increase in series resistance is greater than 5% in the 1000 hours of damp heat testing, the module is not expected to survive for 25 years in Arizona. However, the same module is expected to survive about 25 years in Beijing or Frankfurt even if the Rs of the module degrades by about 15% in the damp heat test because of lower operating temperature in these locations when compared to Arizona. In summary, Figures 4 and 5 illustrates how the acceleration factor and degradation threshold for DH1000 test vary for each location due to differences in weather condition, specifically for the glass/polymer crystalline silicon module with EVA encapsulant.

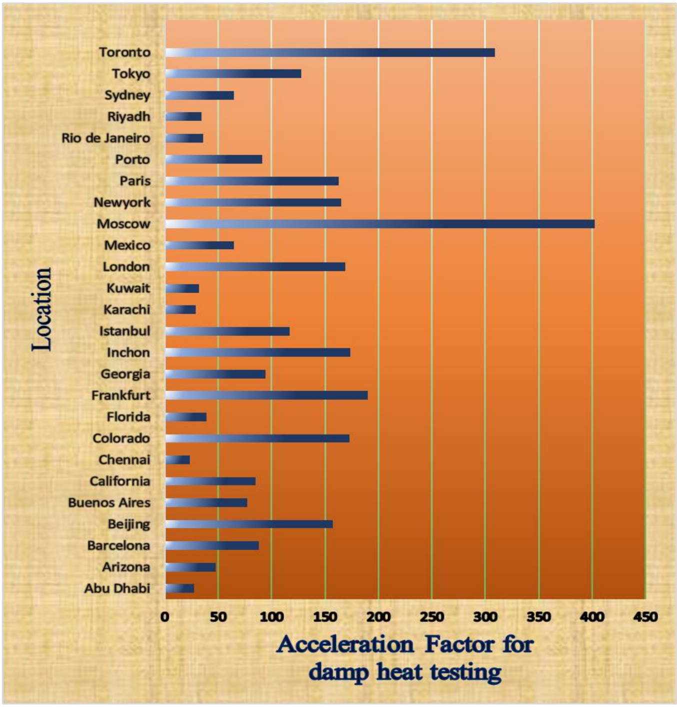

Figure 4: Acceleration factor plot for damp heat testing for 1000 hours at 85℃ and 85 %RH

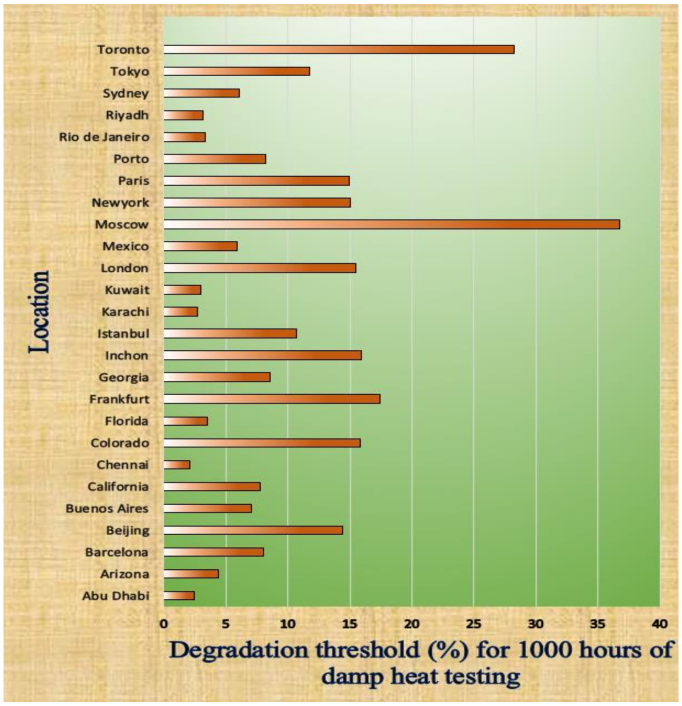

Figure 5: Maximum allowable Rs increase (%) for 1000 hours of damp heat testing corresponding to 25 years equivalent for different regions

5 MODEL VALIDATION AND DISCUSSION

The model performance is validated by predicting the degradation rate for a test site in Arizona. The site had nine modules and the mean Rs increase was 1.96% per year over 18 years in the field. The predicted degradation rate from the estimated Ea value, along with the upper and lower confidence intervals, is summarized in Table 1. Comparing with the actual degradation rate per year in Table 1, the prediction error varies from 10% to 22%.

Table 1: Comparison of predicted Rs degradation rate using estimated Ea of 0.59 ± 0.056eV with actual field measured Rs degradation rate

Site	**Predicted Rs Degradation (% per year)**			**Mean actual Rs degradation (% per year)**
	Ea = 0.53 eV	**Ea = 0.59 eV**	**Ea =0.65 eV**	
AZ	1.52 ± 0.06	1.61 ± 0.06	1.70 ± 0.07	1.96 ± 0.1

The regions like Arizona and Abu Dhabi are dominated by high temperatures such that the module temperature reaches almost equal to that of damp heat chamber temperature especially during summer season. This leads to lower AF values for the hot climatic regions as shown in Figure 4. In addition, the accuracy of the results depends on series resistance calculation using method described in [7], measurement system uncertainty for I-V parameters, and the accuracy of weather data and weather type (hot, humid, cold, dry, etc.). Nevertheless, the approach presented in this work is relatively simple and cost efficient to extract activation energy from the field-to-field data. To avoid outliers, the median values were chosen to alleviate measurement uncertainty since the sample size is low. The measurement system uncertainty for the data used in this study ranges from 1% to 4%.

Future research will be dedicated to quantify the measurement system uncertainty and incorporate cyclic effects of temperature using thermal cycling (TC200) test to study IMS degradation. It is important to remember that a very small variation in activation energy will have a large impact over the acceleration factor. Therefore, it is essential to have a narrow range of confidence interval for activation energy with high accuracy. Also, there exists a research gap to model the degradation behavior of PV modules in both the field and experiment. Due to the rapid evolution of PV industry as well as data analysis techniques, a large amount of data is being collected and analyzed by industry/manufacturers. If these data are made available to the research community, a robust model can be developed. Overall, this paper provides a simple but an acceptable approach to estimate the acceleration factor and determine the field equivalent degradation threshold.

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