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

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SUMMARY & CONCLUSIONS

Acceleration Factor prediction for accelerated life testing of photovoltaic (PV) modules plays a major role in estimating the reliability of modules in 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 of PV modules, complete data on degradation measurement (from qualification testing and field exposure) is not available explicitly and sometimes the accelerated testing standard for some failure modes may not even be established. In such cases, it is hard to design the test plan and determine the degradation threshold or number of hours (or cycles) required to run the accelerated tests for estimating activation energy. This paper presents a novel approach in determining the acceleration factor based on partially available data from field measurements and uses it for damp heat testing of PV modules. Utilizing the available meteorological and degradation data, each field is considered as test environment with varying stress levels and a simple linear model is used for predicting the degradation threshold of DH1000 for field equivalent 25 years. Finally, the results are validated from the known qualification data and the acceleration factor plot for different regions is presented.

1 INTRODUCTION

Over the last decade, there has been an exponential growth of the photovoltaic (PV) industry, due to compelling motivation for conserving fossil fuel energy and the knowledge burst in advancing renewable 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 has 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 complete degradation data in field and limited (or unavailable) qualification test data poses a great barrier. Also, in some cases, when there is lack of established standards for indoor testing of PV modules, then it is of absolute necessity to establish preliminary acceleration factor to design and determine the limit to which the tests should be done.

A brief review of PV degradation modes, analysis, their respective accelerated test procedures, standards and results are summarized in [1, 2]. Usually, the power output (P_{max}) is considered as a qualifying factor, ie., when the output power of a module drops below a certain threshold from initial or nameplate measurement, 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 contributes to maximum power (P_{max}) given in Equation (1), are affected to different degrees with respect to degradation mode and location. By monitoring these parameters, it is possible to quantify various failures occurring in the field.

$$P_{max} = I_{sc} * V_{oc} * FF \tag{1}$$

Hence, measuring P_{max} degradation to study the impact of specific failure mode will not be accurate as P_{max} could be possibly affected by a combination of failure modes. Figure 1 provides a detailed flowchart of P_{max} degradation pathway and the corresponding failure mechanism mainly due to dynamic weather conditions. In this study, Inter Metallic System (IMS) degradation is considered. IMS degradation is one of the major failure mechanisms that occurs in the field-deployed modules and 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, there are four major failure mechanisms like, Inter Metallic Compound (IMC) formation, solder bond degradation, corrosion and loss of contact resistance connected to this failure mode. Dynamic stresses due to varying climatic conditions in the field leads 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.

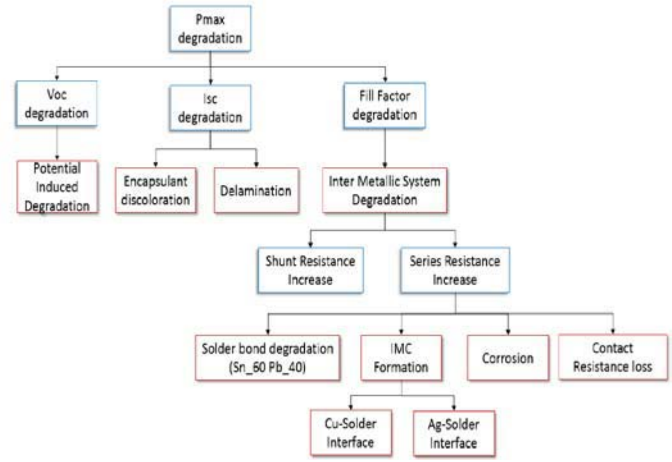

Figure 1: P_{max} degradation flowchart, indicating different components and corresponding degradation parameter

The qualification testing standard IEC 61215 specifies the damp heat test sequence for crystalline-silicon PV modules to be exposed to 1000 hours of 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, thereby limiting the predictive ability of the damp heat model [4]. The problem will become more complex when the test data itself is not available. Also, it is to be noted that a small change in the order of 0.1 eV in activation energy will have a big impact on the acceleration factor. Hence, this paper provides an approach to estimate acceleration factor for global climatic conditions using limited information from field degradation 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 and for various module construction. 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 at Photovoltaic Reliability Laboratory (PRL) at ASU [6] contains I-V and other performance data for 135 modules. In addition to that, 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 NewYork (2 sites) are available at PRL. Figure 2 shows the distribution of series resistance increase per year for field aged modules (20 years) deployed in Arizona.

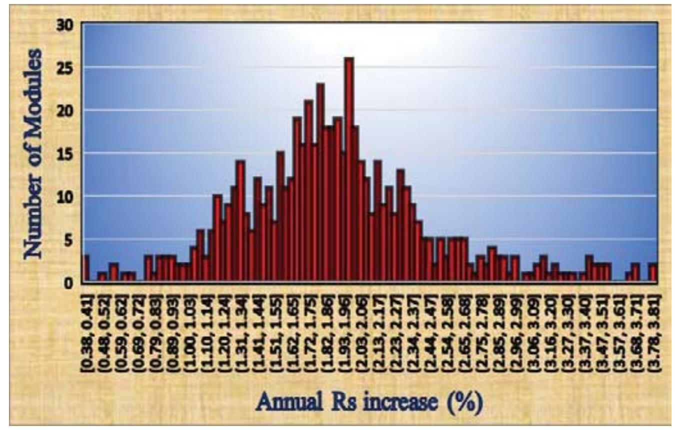

Figure 2: Annual Rs increase (%) for modules installed in Arizona aged 20 years

The series resistance values for modules from both test and field 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 efficient and simple as it involves only ambient temperature and global irradiance.

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

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 20000 modules with different construction type from several manufacturers in the world. The NOCT for polycrystalline modules is distributed normally with mean 46.5℃ and standard deviation of 1.714℃. The module temperature is converted to 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 and final measurement taken after 20 years is available. So, the yearly degradation rate of series resistance is calculated based on the assumption of linear degradation path. There is still research being done to quantify the actual degradation path of PV modules.

2 METHODOLOGY

The construction of PV modules included in this study is glass backsheet laminate 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 to estimate the activation energy and then predict the acceleration factor 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 - 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 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 values of field degradation rates.

As PV modules are exposure to different temperature and humidity levels in Arizona, Colorado, California, and New York, the degradation rate in these fields will not 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, model is fitted by treating degradation rate as dependent variable and climate factors as independent variables to estimate activation energy. Once the activation energy is known, the acceleration factor can be easily calculated. 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 rate available from PRL database. One interesting information at hand is the availability of data from different climate zones like Arizona (hot and dry), New York (cold), Colorado (temperate) and California (temperate). Hence, the model would be able to accommodate for most of the locations across the globe. The results of model fitting and parameter estimation is given in next section.

3 DATA MODELLING AND ESTIMATION

As reported in some literatures [4, 11], the Temperature - Humidity model (Peck's model) was tried but the effect of module humidity for series resistance increase did not seem to be significant. In addition, the adjusted R-squared value did not improve much with the addition of RH factor. A funnel shaped residual plot was observed for inclusion of module humidity, which opposes the constant variance assumption. 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 good fit to the data, confirming that module temperature plays a significant role in series resistance increase. 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

This linear model with respect to all the transformations is compared to Arrhenius's equation given in Equation (5).

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

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 good 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 as described in section 3, the same model can be used to predict the acceleration factor using the available weather data and to find the field equivalent test hours. 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).

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

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 values of T_{acc} is 85˚C and the chamber humidity is 85%. Substituting all the estimated and collected values in Equation (7) using the model in Equation (4) or (6), the mean acceleration factor is determined. Since PV modules will not have much stress due to temperature during nighttime in the field, 1000 hours of daytime maximum temperature is used for this study. Also, majority of the module internal humidity vaporizes due to high module temperature and hence the effect of module humidity for Rs increase is negligible.

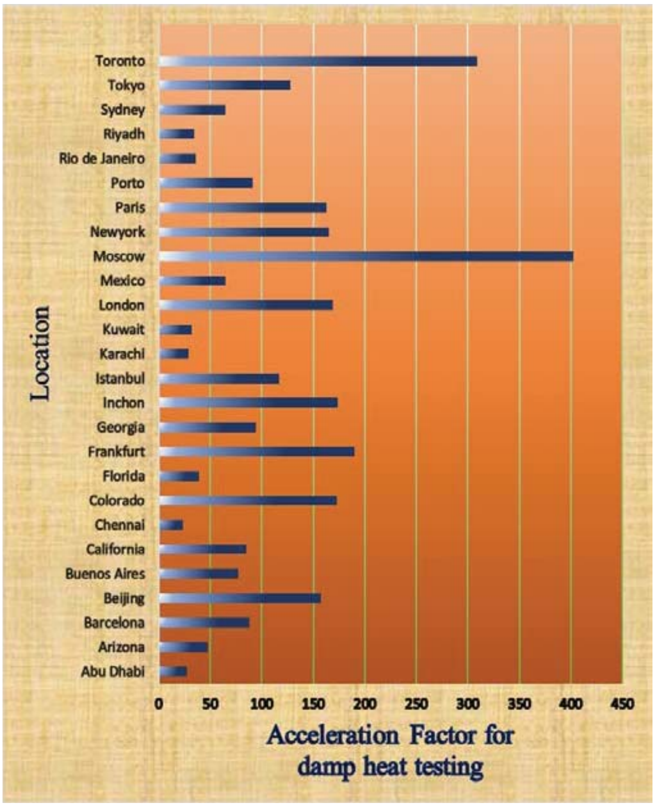

Figure 4: Acceleration factor plot for damp heat testing

Figure 4 shows the acceleration factor plot for different regions using the estimated activation energy. Figure 5 shows the maximum allowable degradation rate for the modules during DH1000 testing in order to survive 25 years. For instance, if increase in series resistance is greater than 1.1% for 1000 hours of damp heat testing, the module will not survive for 25 years in Arizona. However, the same module will survive in Beijing or Frankfurt as the degradation threshold is higher in those locations because of lower temperature when compared to Arizona. Today, most of the C-Si modules from different manufacturers pass 1000 hours damp heat qualification test (which allows for 5% failure threshold) [3], but Figure 5 provides a useful measure to predict module reliability since the degradation rate varies according to climate type. Note that Figures 4 and 5 illustrates how the acceleration factor and degradation threshold varies for each location due to differences in weather condition, specifically for the crystalline silicon module with EVA encapsulant. The results will be more accurate when the model is deployed for exact latitude and longitude of the place that the user is interested to explore.

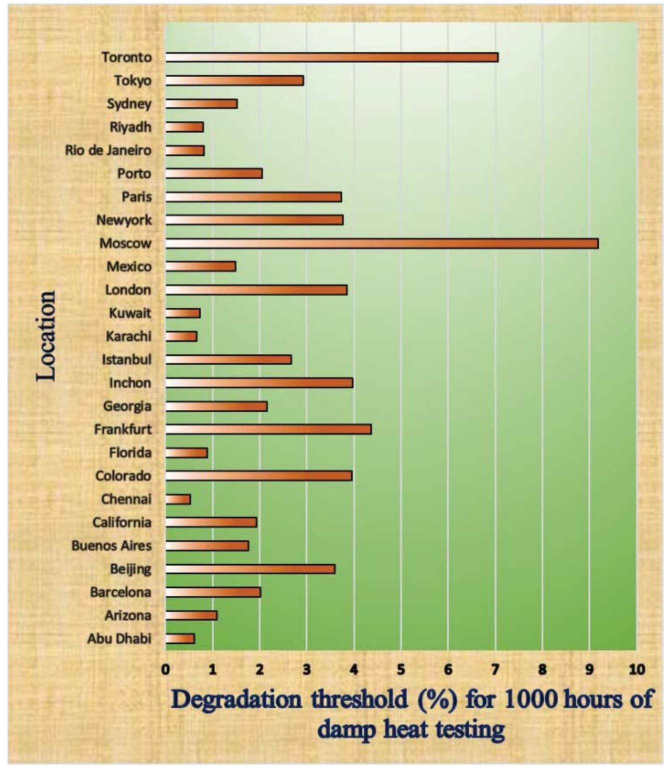

Figure 5: Maximum allowable Rs increase rate (%) for 1000 hours of damp heat testing corresponding to 25 years equivalent for different regions

5 MODEL VALIDATION AND DISCUSSION

The model performance is validated by predicting the degradation rate for a test site at Arizona. The site has 9 modules and the median Rs increase is 1.96% per year. The predicted degradation rate for estimated Ea value along with the upper and lower confidence intervals is summarized in Table 1. It is to be noted that for 1% Rs increase, the fill factor decreases by around 0.2% ~ 0.25% [13]. Since the rate of Rs increase is different, the degradation threshold will vary for FF degradation. Comparing with the actual degradation per year, the prediction error varies from 13% to 25%.

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

Site	Predicted Degradation (% per year)			Median actual degradation (% per year)
	Ea = 0.53 eV	Ea = 0.59 eV	Ea =0.65 eV	
AZ	1.52	1.61	1.70	1.96

The regions like Arizona and Abu Dhabi are dominated by high temperatures such that the module temperature reaches almost equal to that of chamber temperature especially during summer season. This leads to failure modes dominated by temperature, so the AF is low for hot and dry regions 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 IV parameters, and the accuracy of weather data and weather type (hot, humid, cold, dry, etc.). But the approach is relatively simple and cost efficient to extract knowledge from the partially available 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 3.5%.

Future research is to quantify 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 big 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 industries. When these data are made available to research community, a good robust model can be built. Overall, this paper provides a simple but efficient approach to estimate the acceleration factor and determine the field equivalent degradation threshold with availability of limited information.

REFERENCES

1. TamizhMani, G and Kuitche, J. (2013). "Accelerated Lifetime Testing - A Literature Review and Analysis," Solar ABCs.
2. Kuitche, J, Pan, R, and TamizhMani, G. (2014). "Investigation of Dominant Failure Modes for Field-Aged Crystalline Silicon PV Modules Under Desert Climatic Conditions," IEEE Journal of Photovoltaics, 4(3), p:814-826.
3. Wohlgemuth, J, H., Cunningham, D, W, Nguyen, A, M, and Miller, J. (2005). "Long Term Reliability of PV Modules." Proceedings of the 20th European Photovoltaic Solar Energy Conference.
4. Kimball, G, M, Yang, S, and Saproo, A. (2016). "Global acceleration factors for damp heat tests of PV modules." Solar Energy, 96, p: 140-151.
5. EnergyPlus website: "https://energyplus.net/weather"
6. PRL Website: "https://pvreliability.asu.edu/"
7. Dobos, A, P. (2012). "An Improved Coefficient Calculator for the California Energy Commission 6 Parameter Photovoltaic Module Model." Journal of Solar Energy Engineering, (134).
8. Laronde, R, Charki, A and Bigaud, D. (2013). "Lifetime Estimation of a Photovoltaic Module Subjected to Corrosion Due to Damp Heat Testing. Journal of Solar Energy Engineering, (135).
9. California Energy Commission data website: "http://gosolarcalifornia.org/equipment/pv_modules.php"
10. Kempe, M. (2014). Evaluation of Uncertainty in Accelerated Stress Testing, IEEE Photovoltaic Specialists Conference (PVSC).
11. Ndiaye, A., Charki, A., Kobi, A, Kebe, C, M, F., Ndiaye, P, A., and Sambou, V. (2013). "Degradation of Silicon Photovoltaic Modules: A Literature Review." Solar Energy, 96, p:140-151
12. Ndiaye, A., Charki, A., Kobi, A, Kebe, C, M, F., Ndiaye, P, A., and Sambou, V. (2013). "Degradation of Silicon Photovoltaic Modules: A Literature Review." Solar Energy, 96, p:140-151
13. Tummala, A., Oh, J., Tatapudi, S., and TamizhMani, G. (2017). "Degradation of Solder Bonds in Field Aged PV Modules: Correlation with Series Resistance Increase." 43rd IEEE Photovoltaic Specialists Conference (PVSC).

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