LIFETIME ESTIMATION OF A PHOTOVOLTAIC MODULE BASED ON TEMPERETAURE MEASUREMENT

R. Laronde, A. Charki, D. Bigaud
ISTIA-LASQUO, University of Angers - 62 avenue Notre Dame du Lac 49000 ANGERS, France
E-mail (corresponding author): abderafi.charki@univ-angers.fr

Abstract − In the building domain, components or equipment are often subjected to severe environmental conditions. In order to predict the reliability and the lifetime of such equipment, accelerated life testing can be carried out. Severe conditions are applied to accelerate the ageing of the components and the reliability at nominal conditions is then deduced considering that these nominal conditions are not constant but stochastic. In this paper, the accelerated life testing of photovoltaic modules is carried out at severe module temperature levels. The module power losses are monitored and the limit state is determined when a threshold power is reached. The stochastic data and the reliability are simulated during a period of fifty years. Finally, the lifetime of the component is evaluated.

Keywords (Reliability, Lifetime, Photovoltaic, Testing).

1. INTRODUCTION

Photovoltaic modules are used all around the world to produce electricity from solar energy. Manufacturing photovoltaic modules is costly and the components are polluting. To be qualified as renewable energy, they must be reliable and have a long lifetime.

Components lifetime is usually modeled in a deterministic way by considering a constant stress or a predefined mission profile (cf. Figure 1). As for the estimation of the behavior during time or after a given period of time, one commonly uses classical laws such as exponential, Weibull or log normal distribution combined with standard acceleration laws such as Arrhenius, Peck or inverse-power. This article proposes a study of the influence of random environmental conditions on photovoltaic modules performance (energy power). The performance depends largely on weather conditions such as temperature, humidity and UV irradiations which are stochastic. It is also known that these parameters depend on solar time, season and location.

In literature, the reliability evaluation of photovoltaic modules was discussed by Laronde *et al.* [7] and Tsuda [9]. Tsuda [9] and Vázquez [10] who developed accelerated testing programs for crystalline silicon photovoltaic modules using aim tests of IEC 61215 standard [3] (i.e. damp heat testing, thermal cycle testing, UV exposure) and other testing like thermal shock, cyclic illumination and "humidity test" [9].

Wohlgemuth [13] has mainly studied damp heat testing and thermal cycle testing but with time longer or other levels than the standard. However, all the studies have produced neither the relation with the nominal conditions from accelerated life testing nor the stochastic side of nominal conditions.

The lifetime study using stochastic parameters has also been discussed by Voiculescu *et al.* [12] who present statistical and time depending approaches of the reliability in random environment.

In this paper, we present a model developed in order to simulate the influence of parameters on the reliability of photovoltaic modules. The effect of temperature variations is essentially focused. In the proposed approach, Arrhenius acceleration law and Weibull lifetime distribution are used.

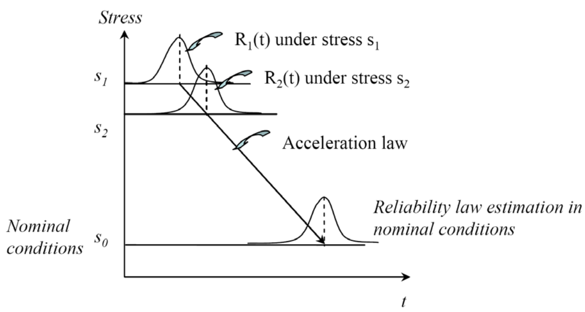

Fig. 1. Reliability assessment with an accelerated testing

2. LIFETIME ESTIMATION

2.1. Lifetime distribution

Weibull distribution is the most popular lifetime distribution. It is used in electronics as well as in mechanics. It is accurate for the three stages of the product life: infant mortality, steady state and wear out period [8]. In this study, we consider that the lifetime distribution of photovoltaic modules [2] can be expressed as:

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{1}$$

with η the scale parameter and β the shape parameter of Weibull law.

2.2. Reliability under constant stress conditions

Arrhenius model is usually used for components when the damaging mechanism is due to the influence of temperature [11]. Thus, Arrhenius model defines the component lifetime τ as (Nelson, 1990):

$$\tau = e^{\gamma_0 + \frac{\gamma_1}{T}} \tag{2}$$

where γ_0 and γ_1 are Arrhenius model parameters and T is the temperature (°K). In Weibull distribution, the scale parameter is the product lifetime, then $\eta = \tau$.

In constant nominal conditions, the temperature T is a constant parameter. After the determination of γ_0 and γ_1, the reliability function becomes:

$$R(t) = e^{-\left(\frac{t}{e^{\gamma_0 + \frac{\gamma_1}{T}}}\right)^{\beta}} \quad (3)$$

This reliability function is related to the power losses of the photovoltaic module. The lifetime which can be calculated by inversion of equation (3) corresponds to the time necessary to reach a target value of power $P_{target}(T) = 80\% \cdot P_{t=0}(T)$.

2.3. Reliability in stochastic conditions

As mentioned in section 1, variables in accelerated life testing models can actually be stochastic in the real-life, which is true when the component is exposed to natural conditions. Thus, to determine the reliability of a component under nominal conditions, three steps must be treated:

- Determining the value of the scale factor and shape factor of the lifetime distribution (Weibull law) for each severe level,
- Calculating parameters γ_0 and γ_1 of the Arrhenius model,
- Transforming reliability functions obtained at severe temperatures $R(t,T_{test})$ into the reliability function at nominal conditions $R(t,T_i)$.

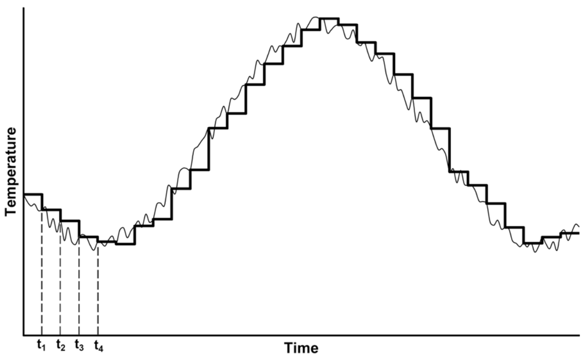

Fig. 2. Stochastic nominal stress

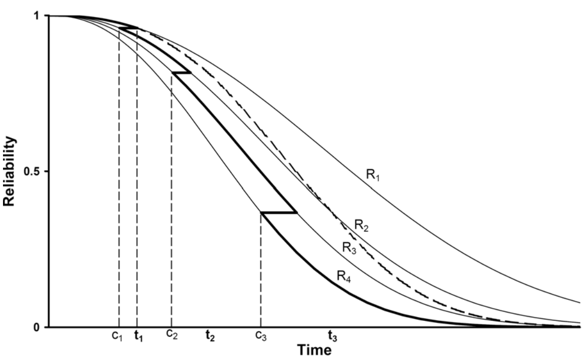

Fig. 3. Reliability of component with stochastic stress

The first step consists in following reliability $R(t,T)$ as a function of time. It allows determining the shape parameter β of Weibull law. As the scale factor η is assumed to depend on the temperature (cf. equation (2)), several reliability curves corresponding to several temperature levels are necessary. Moreover, like the temperature nominal is stochastic with a variation ΔT (as shown in the following section), accelerated life testing are carried out with two several temperature levels and the same variation ΔT to avoid the thermal fatigue effect. The accelerated life testing permits to complete the second step and obtain the Arrhenius model parameters.

The third step aims at transforming the reliability functions obtained at different temperature levels T_{test} into the reliability under nominal conditions T_i (cf. Figures 2 and 3).

If reliability is built incrementally for successive times $t_{i-1} < t \le t_i$, the reliability function $R(t,T_i)$ at nominal conditions becomes [12]:

$$R(t,T_i) = e^{-\left(\frac{(t - t_{i-1}) + c_{i-1}}{\eta(T_i)}\right)^{\beta}} \quad (4)$$

with:

$$c_{i-1} = \eta(T_i) \cdot \sum_{k=1}^{i-1} \frac{t_k - t_{k-1}}{\eta(T_k)} \quad (5)$$

and:

$$\eta(T_i) = e^{\gamma_0 + \frac{\gamma_1}{T_i}} \quad (6)$$

3. SIMULATION DATA

3.1. Module temperature data

The photovoltaic module temperature T_{module} (°K) depends on the ambient temperature T_{amb} (°K) and the solar irradiance G (W/m^2) [5]. It can be expressed as:

$$T_{module} = T_{amb} + \frac{G}{800}\left(T_{NOCT} - 20\right) \quad (7)$$

with T_{NOCT}, the nominal operating cell temperature (°C) obtained with an irradiance of 800 W/m^2, an ambient temperature of 20°C, a wind speed of 1 m/s and a photovoltaic modules inclination of 45° [3].

Irradiance G and ambient temperature T_{amb} are stochastic. Their dependency on time is explained below.

3.1.1. Irradiance

IEC 61725 standard [4] is used to express the irradiance evolution over one day. This standard gives the analytical profile for daily solar illumination (cf. Figure 4) from sunrise to sunset.

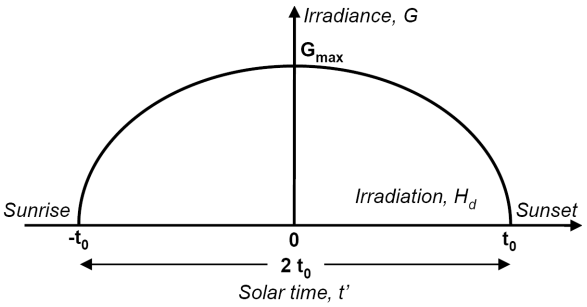

Fig. 4. Analytical profile for daily solar illumination

In Figure 4, G_{max} (W/m^2) is the maximum solar irradiance at solar midday (i.e. t'=0) and H_d (Wh/m^2) is the daily solar irradiation for given photovoltaic modules inclination. The used mean of G_{max} and H_d are thus of meteorological institute in studied location. These values are constant for one day (24 hours).

For $-t_0 \le t' \le t_0$, the expression of G is expressed as:

$$G = \left[\begin{array}{c} G_{max} \cdot \cos\left(\frac{t'}{t_0} \cdot \frac{\pi}{2}\right) \times \\ \left[1 + s \cdot \left(1 - \cos\left(\frac{t'}{t_0} \cdot \frac{\pi}{2}\right)\right)\right] \\ + \xi_G \end{array} \right] \tag{8}$$

where ξ_G is a zero mean random variable and s is the form factor:

$$s = \frac{d \cdot \frac{\pi}{2} - 1}{1 - \frac{\pi}{4}} \tag{9}$$

where d is the canonical factor :

$$d = \frac{H_d}{G_{max} \cdot 2t_0} \tag{10}$$

If meteorological institute does not give the mean daily irradiation H_d, the form factor becomes s=0.

3.1.2. Ambient temperature

In this part, the ambient temperature (T_{amb}) will be formalized in function of the daily temperature (T_{day}) using a sinusoidal form.

The ambient temperature value in the atmosphere depends on the location, the season and the time of the day. For the first two, monthly ambient temperatures recording can be given by national meteorological institutions. For the third part, the ambient temperature evolution over one day must be determined.

The ambient temperature was measured from November 1st, 2008 to December 21st, 2008 every 20 minutes with a thermometer. Results are given in Figure 5.

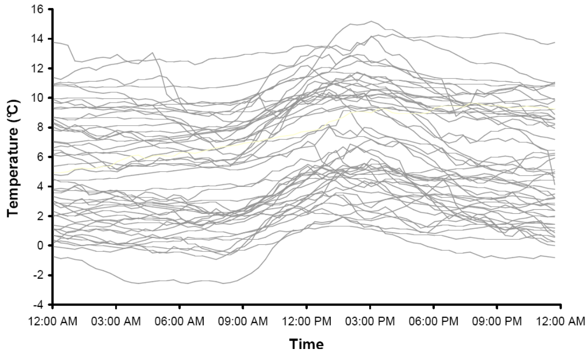

Fig. 5. Measured temperature data

We can see in Figure 5 that the temperature has a great variance. The values of November 2008 permit determining the mean daily temperature T_{day} It follows a normal law for which the mean and the standard deviation are respectively: $\mu_{T_{day}} = 7.52$°C and $\sigma_{T_{day}} = 3.24$°C. To generalize this data, the used mean of T_{day} will be the one provide by the meteorological institute in the studied location. This value is constant for one day (24 hours).

In order to determine the ambient temperature function, the daily temperature is centered on zero as shown in Figure 6.

From these data, the interpolated function of the instantaneous ambient temperature T_{amb} in atmospheric conditions is deduced as:

$$T_{amb} = T_{day} + \frac{\Delta T}{2} \cdot \cos\left(\frac{t' - 2}{t_0} \frac{\pi}{2}\right) + \xi_T \tag{11}$$

where ξ_T is a zero mean random variable and ΔT is the interval between maximum and minimum temperatures during a day (using the measured values, the parameter ΔT follows a normal law with a mean of $\mu_{\Delta T} = 4.23$°C and a standard deviation of $\sigma_{\Delta T} = 1.50$°C).

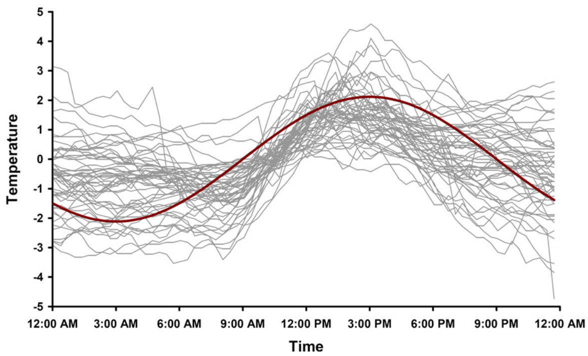

Fig. 6. Temperature data with T_{day} centered at zero.

Equation (11) with ΔT=4°C is plotted in Figure 6 (thick curve). This equation follows the same trend that of the real values.

Finally, for one day, the parameter ξ_T is a zero mean Gaussian random variable with standard deviation of 1.00°C.

3.2. Simulation

Simulink® is used for simulating module temperature and for estimating the time-variant performance. The simulation in Simulink® is separated into two blocks (cf. Figure 7). The first block represents meteorological data using equations in section 3.1. The second block represents time-variant performance using equations in section 2.

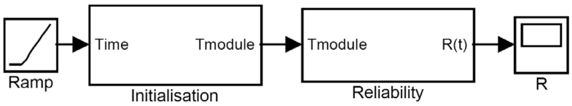

Fig. 7. Simulation with SIMULINK®

3.2.1. Input data

β and t_0 are constant data and they are determined from testing and experience feedback. γ_0 and γ_1, determined by accelerated life testing, are constant data for one simulation and follow a probability distribution for each simulation (γ_0 is a normal random variable and γ_1 a lognormal random variable). Then, T_{day}, G_{max}, ΔT and H_d are constant data during a day and they follow a probability distribution for every day (T_{day}, G_{max} and ΔT are a normal random variables and H_d is constant) with means changing every month. Finally, ξ_T and ξ_G are zero mean random variables.

3.2.2. Output data

Output data of simulation is the time-dependent reliability $R(t)$. The evolution of module temperature T_{module} which is an important intermediate data can also be monitored.

4. APPLICATION ON A PHOTOVOLTAIC MODULE

Table 1 presents the simulated failure times for temperature maintained at two different levels: 100°C (373°K) and 120°C (393°K). These values are chosen to accelerate the degradation because a photovoltaic module has a high temperature operating limit of 90°C and a high temperature destruct limit of 120°C [6].

The lifetime follows a Weibull distribution with $\beta = 2.6$, $\eta_{373°K} = 52078$ h and $\eta_{393°K} = 39102$ h. This permits obtaining the two parameters of the Arrhenius model: $\gamma_0 = 5.23$ and $\gamma_1 = 2102.0$.

In order to provide a confidence level of 90%, Bootstrap method is used [1]. It consists in creating artificial lists by randomly drawing elements from some list of data. Some elements will be used more than once. 500 simulations are carried out thus 500 γ_0 and 500 γ_1 permit determining confidence intervals:

$$1.36 \le \gamma_0 \le 9.09$$
$$1040.4 \le \gamma_1 \le 4247.0 \quad (12)$$

The deviation is very high because only 10 samples are taken into account.

TABLE 1. Accelerating life testing data

i	Failure time (h) at 373°K	Failure time (h) at 393°K
1	18816	14112
2	26880	20160
3	32760	24696
4	37968	28560
5	42840	32088
6	47712	35784
7	52752	39648
8	58464	43848
9	65352	49056
10	76272	57288

TABLE 2. Meteorological data

Month	T_{day} (°C)	G_{max} (W/m²)	H_d (Wh/m²)
January	3.9	316	1910
February	4.7	406	2690
March	7.7	553	4120
April	9.8	599	4880
May	14.2	539	4810
June	17.9	613	5540
July	19.6	708	6060
August	19.6	680	5560
September	15.7	644	4830
October	13.0	473	3240
November	6.9	366	2290
December	4.2	273	1580

Afterward, atmospheric conditions are simulated to have the nominal conditions. The module temperature depends on both the ambient temperature and the irradiance. Thus these two stochastic parameters have been simulated using meteorological data and the simulation developed with Simulink® software.

Meteorological data from Clermont-Ferrand (France) (available on the website PVGIS – Meteorological data for Europe and Africa) have been used (cf. Table 2). Photovoltaic modules have an inclination of 35° and they face the south. Moreover, the photovoltaic module temperature is $T_{NOCT} = 47$°C.

TABLE 3. Random variables

Var.	Units	Law	Mean	Std. dev.
β	-	Constant	2.6	-
γ_0	-	Normal	5.23	2.35
γ_1	°K	Lognormal	2102.0	898.8
t_0	h	Constant	6.0	-
T_{day}	°K	Normal	Cf. table 2	3.5
ΔT	°K	Normal	4.23	1.50
ξ_T	°K	Normal	0.0	1.0
G_{max}	W/m²	Normal	Cf. table 2	80
H_d	Wh/m²	Constant	Cf. table 2	-
ξ_G	W/m²	Normal	0.0	50

For the simulation, the normal law is used for each meteorological variable. H_d is considering constant with values given in Table 2. The standard deviations values of G and G_{max} are chosen by authors. These values can be estimated using measurement data.

Figure 8 shows the photovoltaic module temperature simulated during fifty years. Figures 8 and 9 present the reliability function. Fifty simulations per figure have been performed. For each simulation, the module temperature and the reliability is calculate hour-by-hour.

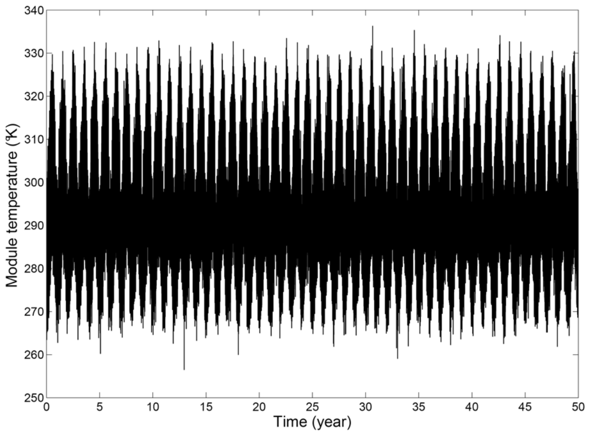

Fig. 8. Photovoltaic module temperature

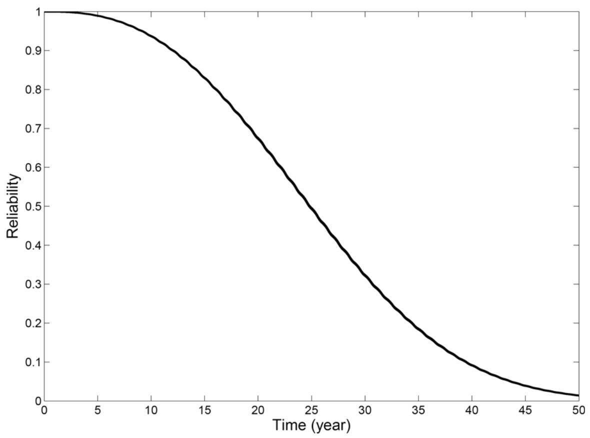

Fig. 9. Photovoltaic module reliability without ALT deviations

In Figure 9, reliability is calculated using γ_0 and γ_1 standard deviations equal at zero. Evolutions of time-dependent reliability are nearly the same. The mean lifetime (MTTF) is 251437 hours ± 422 hours (28.68 years ± 0.05 years) for a confidence level of 90%. That confidence interval and reliability evolutions signify that standard deviations of random variables do not greatly impact the time-dependent reliability and the mean lifetime. We assume that the lifetime distribution of a photovoltaic module follows a Weibull law with a shape parameter $\beta = 2.6$ and the scale parameter $\eta = 251437$ hours.

The warranty time can be estimated using the Figure 9. As manufacturers give a warranty of 20 or 25 years on the module power (80% of initial power), they take a risk of 50.3% for a warranty of 25 years and a risk of 32.4% for a warranty of 20 years. That's to say 32.4% of the production risks to be change 20 years after the installation if power testing are realized at the installation and 20 years later.

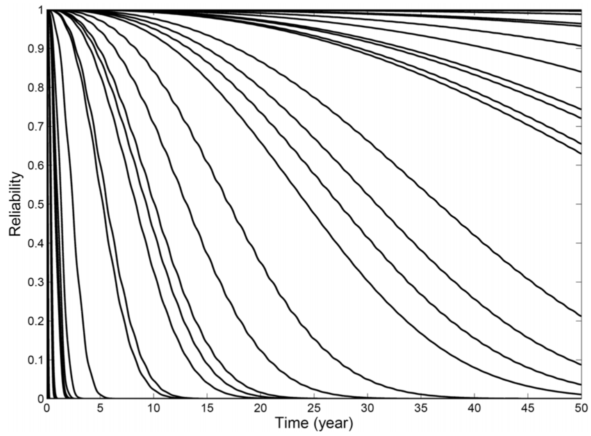

Fig. 10. Photovoltaic module reliability with ALT deviations

In another way, when γ_0 and γ_1 standard deviations are taken into account, evolutions of time-dependent reliability are very different (cf. Figure 10). That is due to the uncertainty-spreading of an accelerated life testing and a large deviation of parameter due to Bootstrap method. With this way, the σ/μ ratio is upper than 40% using 500 simulations.

3. CONCLUSION

This article presents a methodology for the evaluation of the reliability of a photovoltaic module, which is subjected to a stochastic condition: the module temperature depending on ambient temperature and irradiance. Some manufacturers announce a photovoltaic modules lifetime of 25-30 years and we obtained finally a lifetime of 29 years thus simulated data of table 1 seem to be correct. However, failure times of accelerated life testing are very long (nearly 9 years for the testing at 100°C and more of 6 years for the other). A manufacturer can not be realize testing during 10 years because it is so expensive and it can not be wait long since to sell photovoltaic modules. We must reduce the accelerated life testing time. Several methods exist to do this.

It would be interesting to higher the temperature to decrease the testing-time but it is impossible because photovoltaic modules have a technological limit at 120°C (393°K). In a different way, it would be possible to do a testing plan with censure. The testing-time would be determined before testing and the reliability would be calculated using the likelihood method. Finally, the likely method to reduce the testing-time is to take into account other parameters like relative humidity and UV radiation; other acceleration law would be used in these cases.

Moreover, using the accelerated life testing uncertainty, the lifetime estimation gives a standard deviation very high and it is impossible to conclude with this data only. It would be possible to reduce this variability by carrying out another test with another temperature. To reduce this variability, a value close to the mean nominal module temperature can be taken.

ACKNOWLEDGEMENT

This research was supported by the "Région Pays de la Loire" (a French region). This support is gratefully acknowledged.

REFERENCES

[1] P. Compere: "Détermination des intervalles de confiance d'une loi de survie par la méthode du Bootstrap", *Revue de statistique appliquée*, 45(2), 1997, pp. 21-37.
[2] F. Guérin, P. Lantieri, B. Dumon: "Applying accelerated life models to halt testing", *9th ISSAT International Conference on Reliability and Quality Design*, 2003.
[3] IEC 61215: "Crystalline silicon terrestrial photovoltaic (PV) modules – Design qualification and type approval", 2005.
[4] IEC 61725: "Analytical expression for daily solar profiles", 1997.
[5] R.P. Kenny, E.D. Dunlop, H.A. Ossenbrink et al.: "A practical method for the energy rating of c-Si photovoltaic modules based on standard tests", *Progress in Photovoltaics: Research and Applications* 14(2), pp. 155-166, 2006.
[6] G. Kern: "SunSine™300: Manufacture of an AC Photovoltaic Module", *Final Report Phases I & II. NREL*, 1999.
[7] R. Laronde, A. Charki, D. Bigaud: "Reliability of photovoltaic modules based on climatic measurement data", *The International Journal of Metrology and Quality Engineering*, Vol. 1, April 2010.
[8] W.B. Nelson: "Accelerated Testing: Statistical Models, Test Plans and Data Analyses", *Wiley-Interscience*, 1990.
[9] I. Tsuda, S. Igari, K. Nakahara et al.: 2003. "Long term reliability evaluation of PV module", *3rd World Conference on Photovoltaic Energy Conversion* B, pp. 1960-1963, 2003.
[10] M. Vázquez, I. Rey-Stolle:"Photovoltaic module reliability model based on field degradation studies", *Progress in Photovoltaics: Research and Applications,* 16(5), pp. 419-433, 2008.
[11] S. Voiculescu, F. Guerin,, M. Barreau, A. Charki: "Bayesian estimation in accelerated life testing", *International Journal of Product Development,* 7(3-4), pp. 246-260, 2009.
[12] S. Voiculescu,, F. Guerin, A. Charki,, M. Barreau: "Reliability estimation in random environment: Different approaches", *RAMS 2007*, pp. 202-207, 2007.
[13] J.H. Wohlgemuth, D.W. Cunningham, M. Nguyen et al.: "Long term reliability of PV modules", *20th European Photovoltaic Solar Energy Conference*, pp. 1942-1946, 2005.

Authors:
R. Laronde, PhD Student, ISTIA-LASQUO, University of Angers, 62 avenue Notre Dame du Lac, 49000 Angers, tel. +33241226500, fax. +33241226521, remi.laronde@univ-angers.fr
A. Charki, Associate Professor, ISTIA-LASQUO, University of Angers, 62 avenue Notre Dame du Lac, 49000 Angers, tel. +33241226500, fax. +33241226521, abderafi.charki@univ-angers.fr
D. Bigaud, Professor, ISTIA-LASQUO, University of Angers, 62 avenue Notre Dame du Lac, 49000 Angers, tel. +33241226500, fax. +33241226521, david.bigaud@univ-angers.fr