Research Article| Submit Manuscript

Turkish Journal of Electromechanics & Energy

ISSN-2547-975X

Lifetime Estimation Method for Photovoltaic Generators

M. Hassan Ali[1, 2*], A. Mehmood[3], S. Haddad[4]

[1]MIS Laboratory, University of Picardie Jules Verne, Amiens, France
[2]Doctoral School, University of Djibouti, Djibouti-city, Djibouti
[3]Faculty of Mechanical Engineering, University of Engineering and Technology, Lahore, Pakistan
[4]Renewable Energy Laboratory, University of Jijel, Jijel, Algeria

Received: 17 November 2018; Revised: 20 March 2019; Accepted: 27 March 2019; Published: 30 June 2019
Turk J Electrom Energ Vol.: 4 No: 1 Page: 3-10 (2019)
SLOI: http://www.sloi.org/
*Correspondance E-mail: mohamed.hassan.ali@u-picardie.fr

ABSTRACT This article addresses a methodology to evaluate the lifetime of photovoltaic generators (*PVGs*) by extracting parameters from a Weibull distribution and using the Akaike criterion test. A degradation index is developed for outdoor photovoltaic generators affected by operating conditions. Degradation index quantification, through weather monitoring (T_i ; G_i) and instantaneous continuous output power, is proposed. For this purpose, statistical data series are extracted that correspond to the instantaneous number of contributing *PVGs*, which allows a reliability study. Akaike Criterion Test (*AIC*) shows that these data series tend towards a Weibull distribution. Efforts are made to be able to quantify the parameters of the distribution model and thereby obtain the lifetime of the *PVG*. The approach is validated by using data from several *PVGs*.

Keywords: Modelling, Prognosis, Akaike Criterion Test, Parameters Estimation, Weibull Distribution

Cite this article: M. Hassan Ali, A. Mehmood, S. Haddad, Lifetime Estimation Method for Photovoltaic Generators, Turkish Journal of Electromechanics & Energy, 4(1), 3-10, (2019).

1. INTRODUCTION

Nowadays, the future of renewable energy is undisputed. Among these sources of renewable energy, solar energy harnessed through Photovoltaic (*PV*) modules is increasingly performant. However, until today, the electrical production of many *PV* installations is not monitored with tools and functions of prognosis and diagnosis to obtain the best possible efficiency. It is well known that without a control function, the presence of faults can cause power losses, but they could also lead to safety risks that could significantly reduce the performance of the *PV* system.

The evolution of degradation with respect to operating conditions impacts the behavior of the system. Numerous studies on photovoltaic generator (*PVGs*) in outdoor environments have confirmed performance degradation [1]. Prognosis approaches discussed by Byington et al. [2] can be categorized into three levels: experience-based methods, data-based, and model-based. As shown in Figure 1, applicability and cost & accuracy change respectively per used prognostic methods.

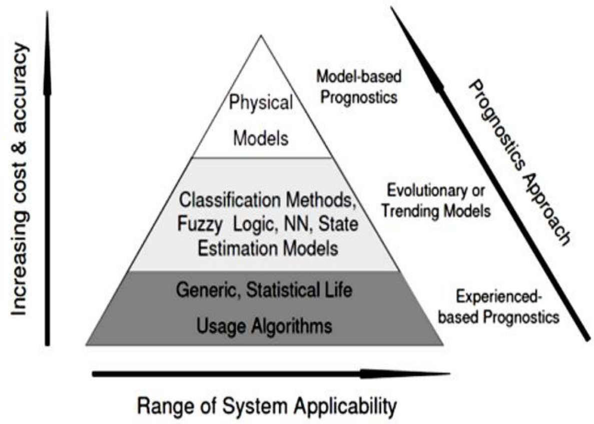


Fig. 1. Classification of prognosis approaches

The direct or indirect measurement of the state of degradation represents an important knowledge for the prognosis evaluation [3]. The selection of a prognosis approach depends mainly on available information about the considered system [4]. Formally, the prognosis is defined as the ability to predict the lifespan of a system. This lifespan indicates the remaining time before the system cannot perform its main functions. In the considered system, this lifespan figure will be estimated under specific operational conditions and random environmental conditions that can cause faults and aging. Indeed, a system can be affected by abnormal events which accelerate or not it's aging process, and by such means reduce its lifetime [1]. Osterwald and McMahon [5] used population data to obtain a distribution model to estimate the degradation rate of the PV modules. Vazquez and Rey-Stolle also proposed to model the power probability density of a *PVG* with an exponential distribution [6]. These authors demonstrated the possibility of modeling the data acquired from *PVGs* by means of statistical distributions. In this way, we propose an approach to calculate the *PVG* lifetime by using a distribution model developed using actual *PVGs* data series [7]. The proposed approach follows the well-known approaches by Pan and Crispin [8], Monroe and Pan [9] and Wohlgemuth et al. [10], but it uses real data series rather than the extracted model from Accelerated Life Test (*ALT*) tests. The following sections relate to time series extraction used to calculate *PVG* lifespan.

Our study uses monitoring data from two photovoltaic plants and their MATLAB/Simulink models. For this purpose, we extract meteorological data from the *PV* plants to evaluate the maximum power signal by simulation. Then, we propose a reliability model to calculate the photovoltaic power plants lifespan. This approach is useful for reducing maintenance, and allowing optimization of operating conditions.

2. PROPOSED APPROACH

2.1. Extraction of Time Series

A statistical analysis method is proposed to use the data series extracted by monitoring the *PV* power stations and to confirm the impact of environmental conditions. This is a transposition of the data from the monitoring to obtain usable statistical series for lifetime determination.

The statistical series are aimed to be obtained by transposing the actually recorded data from the *PV* system into a total that represents surviving or failing modules (i.e. statistical series). The model used, proposed by Notton et al. [11], provides ideal performance in terms of maximal output power without considering environmental effects or faults. It follows the polynomial form as stated in Equation (1) below [11]:

$$P = \eta_{ref} \times A \times G \times \begin{bmatrix} 1 - \beta_{ref} \times (T_i - T_{ref}) + \\ \gamma_{ref} \times log\, G_i \end{bmatrix} \quad (1)$$

The output power of the *PV* system is obtained using an approach based on the model defined through Equation (1) in which faults or aging effects are not considered. Obtained outputs with the MATLAB/Simulink model are shown in Figure 2 (b) and acquired actual weather condition in Figure 2 (a).

The produced maximal power by each *PVG* for the weather condition $(T_i\,;\,G_i)$ is done by:

$$P_{i_{maximal\_PV\_Syst}} = f(T_i\,;\,G_i) \quad (2)$$

$$P_{i_{maximalperunit}} = \frac{P_{i_{maximal\_PV\_Syst}}}{Number_{installedmodules}} \quad (3)$$

Considering that the actual power provided by *PV* systems has been obtained from the system's monitoring ($P_{i_{measured\_PV\_Syst}}$) and by Equations (2) and (3), then the number of instantaneous contributing *PVGs* ($N_{I\_C\_PVG}$) can be determined for each of meteorological conditions $(T_i\,;\,G_i)$ using:

$$N_{I\_C\_PVG} = \frac{P_{i_{measured\_PV\_Syst}}}{P_{i_{maximalperunit}}} \quad (4)$$

Measured real power divided by maximal estimated power per unit, gives the number of instantaneous contributing *PV* modules. Thus, the number of the surviving modules (i.e. contributing modules) can be found by Equation (4). Compared to the total number of installed modules, we can deduct the number of failing modules. This method is based on the reliability analysis of population under the same operating conditions and stress [12]. Indeed, we have a population of identical modules affected by the same operating environment from the *PVG* level to the entire photovoltaic plant level. With this constraint and by using exactly the same *PVGs*, we can obtain statistical data series in Equation (4). Under these two assumptions, a reliability analysis to predict *PVG* lifespan becomes possible.

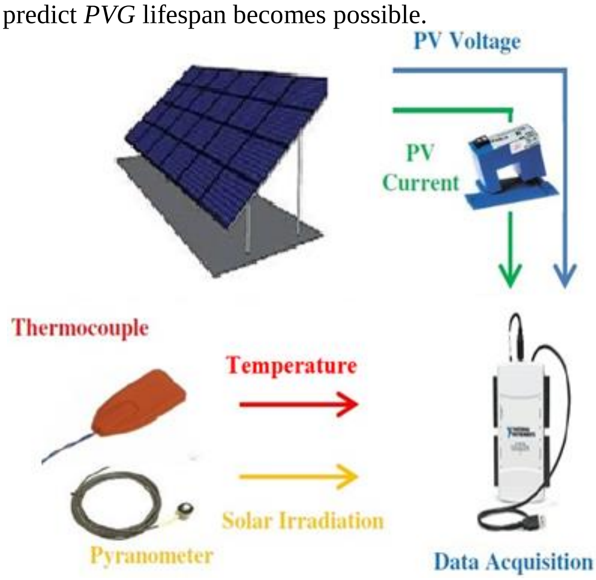


Fig. 2 (a). Real-time data acquisition for each *PV* plant

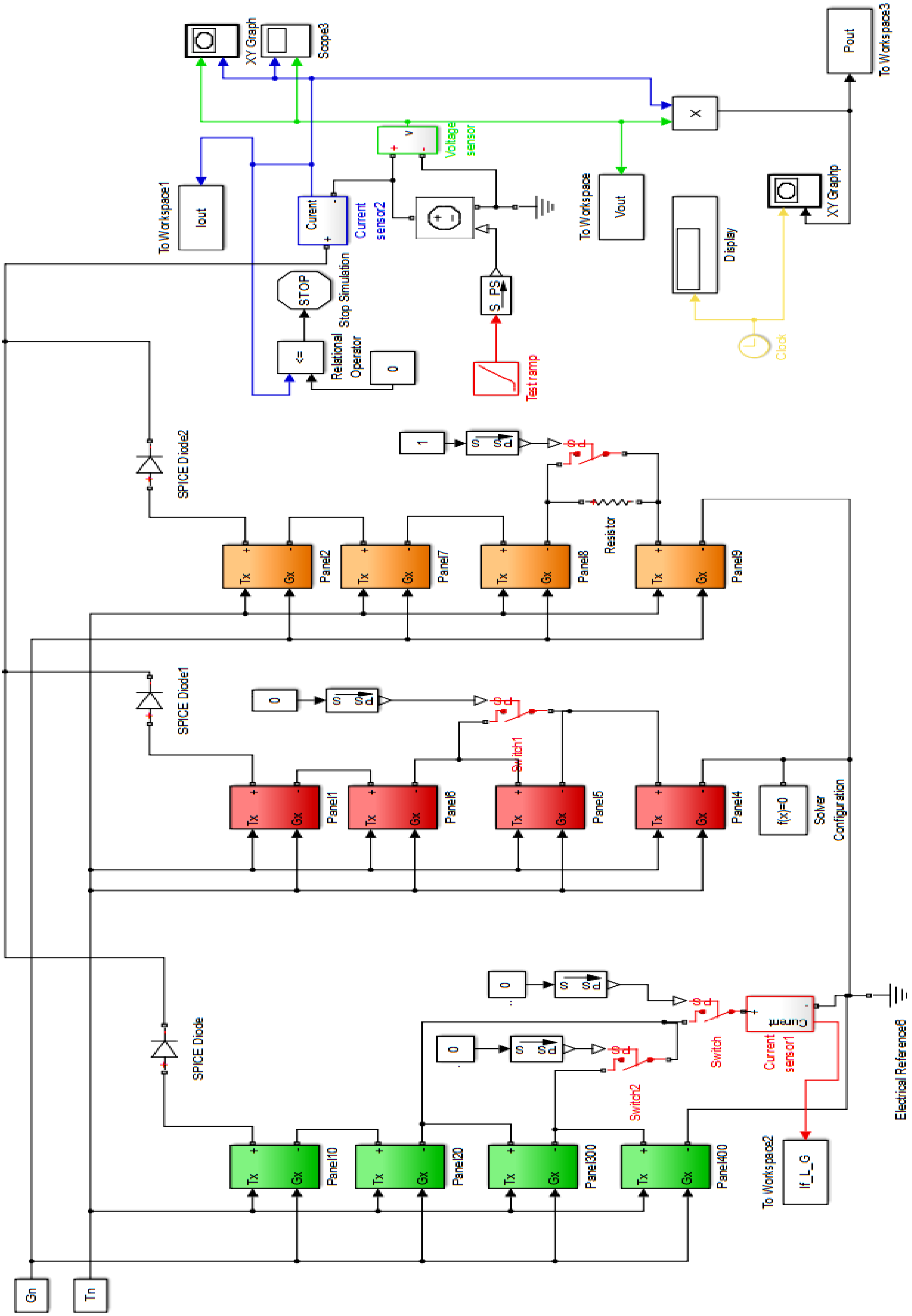


Fig. 2 (b). MATLAB/Simulink model adapted for each *PV* plant

2.2. Akaike Information Criterion and Candidate Distribution Set

Akaike information criterion (*AIC*) is a quality measure of statistical models proposed by Akaike [13]. This information criterion is based on a trade-off between precision and model complexity. It penalizes the model according to the number of parameters to satisfy the parsimony criterion. This test represents a compromise between the bias, which decreases with the number of parameters, and the parsimony, that describes data with fewest parameters. The interval between data and tested model is approximated using Kullback-Leibler divergence [13]. This criterion is noted as *AIC* and defined by the following relation:

$$AIC = -2 \times log(L) + 2 \times k \tag{5}$$

where: L is the maximized likelihood of data and k the number of model parameters.

From the set of candidate models, the chosen model is the one that will have the lowest *AIC* value. In our case, it compares the selected data from Equation (4) with four classical distributions (i.e., χ^2, Exponential, Beta, Weibull) which have known properties [12]:

- χ^2 Distribution :

$$f(x;k) = \frac{\left(\frac{1}{2}\right)^{\frac{k}{2}}}{\Gamma\left(\frac{k}{2}\right)} \times x^{\frac{k}{2}-1} \times e^{-\frac{x}{2}} \tag{6}$$

Where: k is degrees of freedom, x is for independent random variables and $\Gamma(n) = \int_0^{\infty} e^{-x} \times x^{n-1} dx$

- Exponential Distribution :

$$f(x;\lambda) = \begin{cases} 0, & x < 0 \\ \lambda \times e^{-\lambda x}, & x \geq 0 \end{cases} \tag{7}$$

With: > 0 : intensity parameter.

- Beta Distribution :

$$f(x;\alpha,\beta) = \begin{cases} 0, & else \\ \dfrac{x^{\alpha-1} \times (1-x)^{\beta-1}}{\int_0^1 u^{\alpha-1} \times (1-u)^{\beta-1} du}, & if\ x \in [0,1] \end{cases} \tag{8}$$

Where(α, β) are two positive shape parameters.

- Weibull Distribution:

$$f(x;\beta,\eta) = \frac{\beta}{\eta} \times \left(\frac{x}{\eta}\right)^{\beta-1} \times e^{-\left(\frac{x}{\eta}\right)^{\beta}} \tag{9}$$

Where $(\eta, \beta)$are shape and scale parameters.

The Akaike criterion makes it possible to test the calculated statistical data series against monitored data, to identify the most suitable distribution model. Selection will be made among four candidate distribution models described by Equations (6), (7), (8), and (9). Subsequently, we can extract the parameters of the selected model to estimate the lifespan of a *PV* system [12].

2.3. Estimation of Distribution Parameters by Maximum Likelihood Method

In this approach, we estimate the parameters of the selected distribution model by using the maximum likelihood method. It consists of looking for a theoretical model that maximizes the probability density of the observed data. For example in the case of Weibull law, the parametric values that maximize the product:$\prod_{i=1}^{n} f(x_i)$ for the n operating times obtained from previous series. This method gives us:

$$L(\beta,\eta) = \prod_{i=1}^{n} \frac{\beta}{\eta} \times \left(\frac{x_i}{\eta}\right)^{\beta-1} \times e^{-\left(\frac{x_i}{\eta}\right)^{\beta}} = \left(\frac{\beta}{\eta}\right)^{n} e^{\left(-\sum_{i=1}^{n}\left(\frac{x_i}{\eta}\right)^{\beta}\right)} \prod_{i=1}^{n} \left(\frac{x_i}{\eta}\right)^{\beta-1} \tag{10}$$

We can maximize this function by maximizing its logarithm:

$$\ln[L(\beta,\eta)] = \ln\left[\left(\frac{\beta}{\eta}\right)^{n} e^{\left(-\sum_{i=1}^{n}\left(\frac{x_i}{\eta}\right)^{\beta}\right)} \prod_{i=1}^{n} \left(\frac{x_i}{\eta}\right)^{\beta-1}\right] \tag{11}$$

$$\ln[L(\beta,\eta)] = n \times ln\left(\frac{\beta}{\eta}\right) - \eta^{-\beta} \sum_{i=1}^{n} x_i^{\beta} + (\beta - 1) \sum_{i=1}^{n} ln\left(\frac{x_i}{\eta}\right) \tag{12}$$

The estimation of parameters ($\eta; \beta$) are finally obtained mathematically as follows:

$$\begin{cases} \dfrac{\partial \ln[L(\beta,\eta)]}{\partial \beta} = 0 \\ \dfrac{\partial \ln[L(\beta,\eta)]}{\partial \beta} = 0 \end{cases} \tag{13}$$

We obtain the two following equations whose resolution permits to estimate parameters ($\eta; \beta$):

$$\begin{cases} n \times \frac{1}{\beta} - \frac{1}{\eta^{\beta}} \times \sum_{i=1}^{n} x_i^{\beta} \times \ln\left(\frac{x_i}{\eta}\right) + \sum_{i=1}^{n} \ln\left(\frac{x_i}{\eta}\right) = 0 \\ -n \times \frac{1}{\eta} - \frac{\beta}{\eta^{\beta+1}} \times \sum_{i=1}^{n} x_i^{\beta} + (1-\beta) \times n \times \frac{1}{\eta} = 0 \end{cases} \tag{14}$$

This method allows us to obtain the parameters of distribution selected in Equation (9) Weibull law section and will be used for lifetime determination.

2.4. Lifetime Determination

The relevance of modeling was established with Akaike criterion test which allows selection of the most suitable classical law among the available four following candidates: $\chi 2$, Exponential, β, Weibull [13]. Then, we can obtain the lifespan of the *PV* system according to [12] with the following relation:

$$MTTF(t) = \eta \times \Gamma\left(\frac{1}{\beta} + 1\right)$$

$$\text{With : } \Gamma(n) = \int_0^{\infty} e^{-x} \times x^{n-1} dx \tag{15}$$

3. RESULTS AND DISCUSSION

The proposed methodology, described in Figure 3, is applied to determine the lifespan of the *PV* system using monitoring data provided by the International Energy Agency report [14]. We have focused on Localnet as shown in Figure 4 and Liestal as shown in Figure 5 *PV* plants for the validation of the proposed method. These two *PV* plants were developed using polycrystalline technology, whose performances have been monitored for 163 months and 155 months respectively as shown in Figure 6 and Figure 7. By using polynomial *DC* power model (elaborated through equation (1)) and information from the structure of these *PV* plants in Table 1, we have developed a MATLAB/Simulink model without faults and aging, which provides the instantaneous maximal power for recorded meteorological condition $(T_i; G_i)$[15].

In both presented cases, models slightly overestimate experimental data with low mean bias error (*MBE*) and a high degree of approximation, low root mean square error *(RMSE*), as shown in Table 2. The accuracy of the models shown in Figure 6 and Figure 7 is crucial for the determination of the time series. The evolution of blue curves (Figures 6 and 7) shows electrical production in two different environments. We can see both seasonality of solar radiation and the effects of major breakdowns that appear during signal monitoring. Our approach allows to consider all unfavorable factors together for electrical production and calculate *PV* plant lifetime.

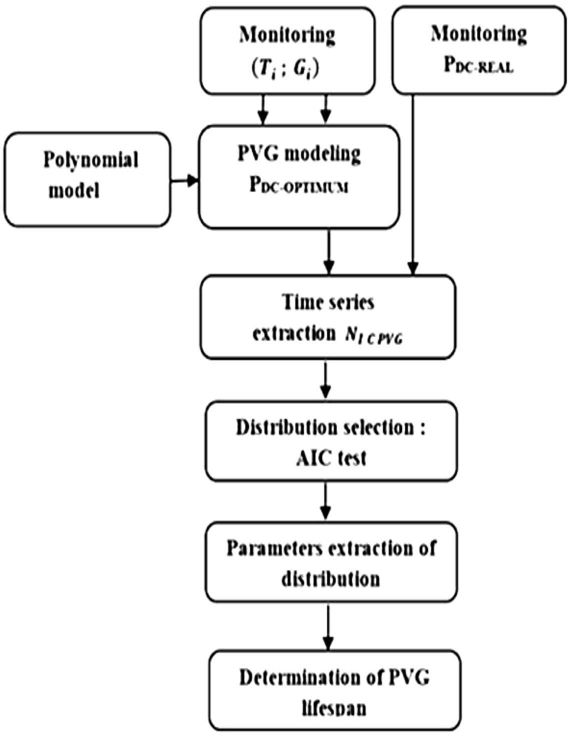


Fig. 3. Flowchart of the evaluation method for *PVG* lifetime

Using the MATLAB/Simulink model shown in Figure 2(b) and the recorded actual data for each case of the considered *PV* systems, the number of instantaneous maximal contributing modules, $N_{I\_C\_PVG}$ is extracted through Equation 4.

Table 1. Data and locations of the two PV plants

PV plant	*Localnet*	*Listal*
Types and technologies	Solarex MSX 120 Poly-Si	Kyocera LA361H51 Poly-Si
Latitude	47.06	47.29
Longitude	7.61	7.44
Height (meter)	530	327
The angle of inclination (degree Celsius)	30	30
Efficiency (%)	10.8	11.67
Module area (m^2)	1.112	0.437
Number of modules	136	363

By using Equation 5, the Akaike criterion test permits selection among four candidate statistical distributions, presented in section II, and then classifies them [16]. Table 3 presents calculated values for the four distributions. The weakest *AIC* values are obtained with Weibull models.

Indeed, these two statistical data series for two power stations respectively, exhibit similar behavior to Weibull distributions, as depicted in Figures 8 and 9.

Table 2. Determination of MBE and RMSE errors.

Errors	*MBE*	*RMSE*
PV plant in Liestal	0.0016214	0.3773
PV plant in Localnet	0.0054489	0.2763

Once the model has been chosen, the parameters of the two Weibull distributions are extracted for each case. Calculated results are presented in Table 4. Finally, the life span of PV plants is estimated in real time depending on the effects of the environment (aging effects and faults). This method depends mainly on data provided by the monitoring sensors. As acquisition progresses, it becomes more precise. Indeed, the knowledge of the remaining lifespan becomes important in the second part of the life cycle of PVG, i.e. after 20-25 years. Our method with acquired data allows a better knowledge of the performance and real-time estimation of PVGs lifetime.

Table 3. *AIC* values for four candidate distributions on both sites.

Weibull distribution parameters	*Shape* β	*Scale* λ	*MTTF (months)*
PV plant Localnet	32.62	120.04	118.02
PV plant Liestal	11.89	250.33	239.81

Table 4. Extraction of Weibull parameters and *MTTF* determination.

Candidates distributions	*AIC values (Localnet case)*	*AIC values (Liestalcase)*
β	0.545	3.88
χ^2	614.801	595.95
Weibull	-185.146	-180.582
Exponential	59.646	100.656

Fig. 4. (a) *PV* plant Localnet, Burgdorf (Switzerland) (b) *PV* plant EBL Liestal (Switzerland) [14].

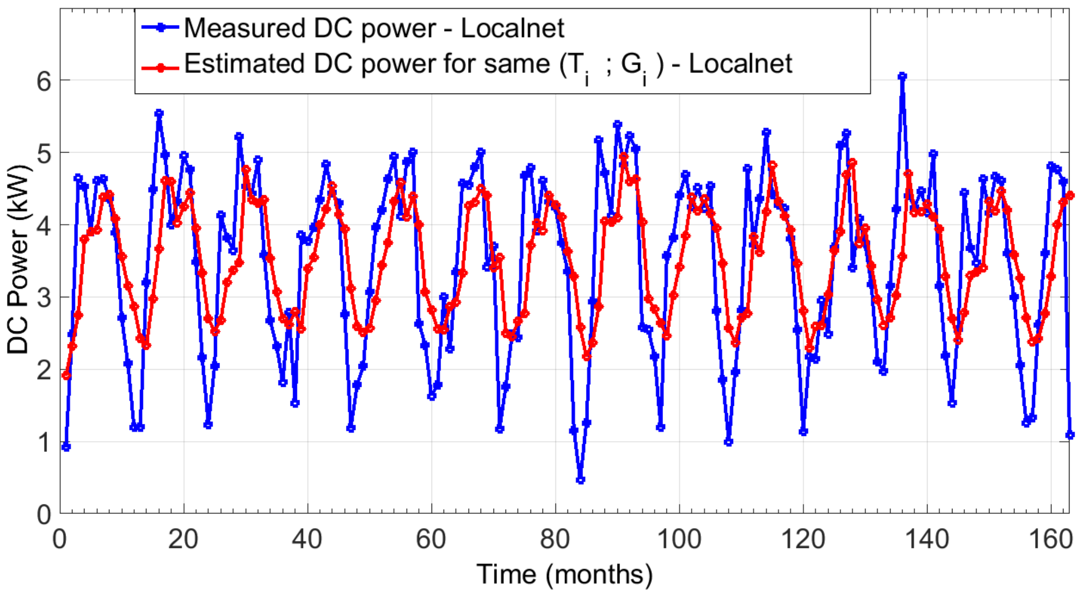


Fig. 5. Comparison between measured and estimated power for Localnet *PV* plant.

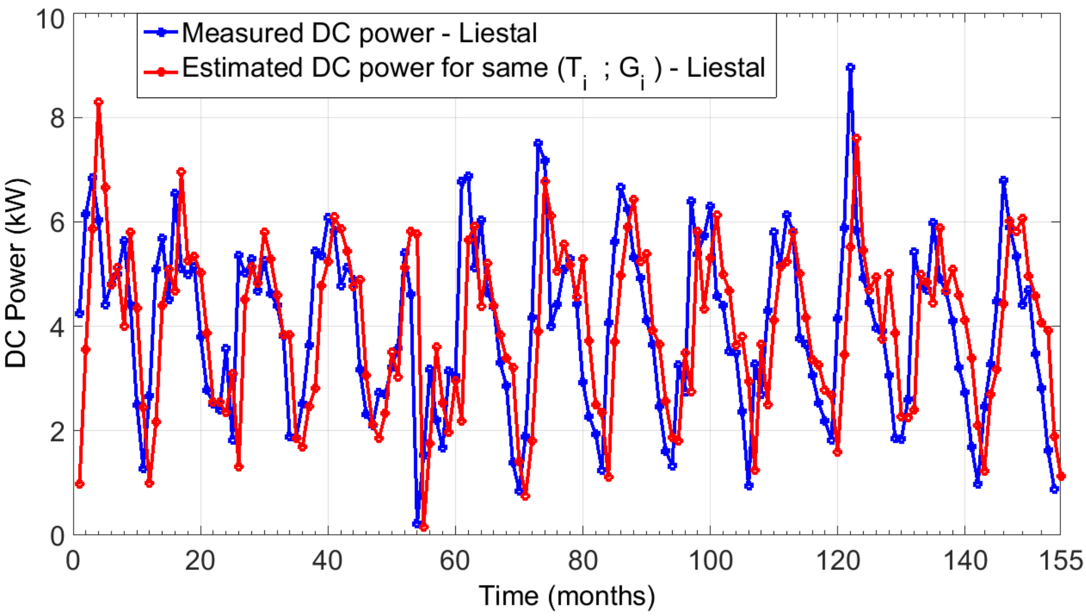
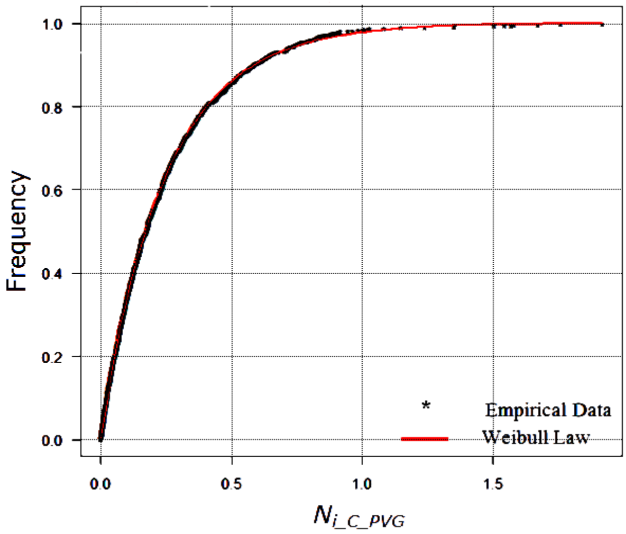
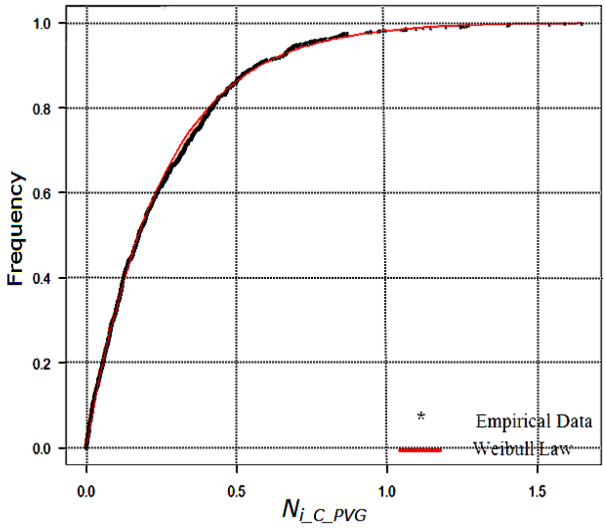


Fig. 6. Comparison between measured and estimated power for Liestal *PV* plant.



(a)



(b)

Fig. 7. Comparison between empirical distribution of $N_{I\_C\_PVG}$ and it's Weibull law for: (a) Localnet / (b) Liestal.

4. CONCLUSION

In this article, we present an approach to estimate the lifespan of a *PV* system in real time. It is a method based on reliability analysis models. First, with the MATLAB/Simulink model, we obtained maximal power of each considered *PVG* without considering the effects of environmental degradation. Then, by correlating it with measured power, we can extract time series corresponding to the number of maximal contributing *PVGs*. A Weibull law, validated by Akaike criterion test, allows modeling such time series. This criterion is known to have a predictive tendency and it allows to our approach to anticipating the trend based on current data. Subsequently, the parameters are extracted using obtained Weibull distributions in each considered case.

Finally, with these extracted parameters, *MTTF* can be calculated, that would lead to the estimation of considered *PV* system lifetime. Obtained values correspond to 118.02 months (9.83 years) for Localnet site and to 239.81 months (19.9 years) for Liestal site. They correspond to the assertion of manufacturers who foresee a maximum lifetime of 264 months. Lifetime results come from truncated data, limited to data already acquired. This can limit the method accuracy. Furthermore, occurrences of serious faults can reduce this expected lifetime, as for Localnet, to less than half duration. However, this approach makes it possible to evaluate in real time impacts of environmental conditions and degradations from operating conditions on a *PV* system lifetime.

Appendix

AIC	Akaike criterion test
PV	Photovoltaic
PVG	Photovoltaic generator
DOF	Degrees of freedom
MBE	Mean bias error
MTTF	Mean time to failure
RMSE	Root mean square error
η_{ref}	Efficiency of the module at reference temperature T_{ref}
T_{ref}	Reference temperature (25 °C).
β_{ref}	Temperature coefficient at reference temperature T_{ref} (°C^{-1})
γ_{ref}	Absorption coefficient at reference temperature T_{ref}
A	Module Area (m^2).
T_i	Measured instantaneous temperature (°C).
G_i	Measured instantaneous irradiance (W.m^{-2}).

REFERENCES

[1] E. D. Dunlop, D. Halton, The performance of crystalline silicon photovoltaic solar modules after 22 years of continuous outdoor exposure, Progress in photovoltaics, 14(1), 53-64, (2006).
[2] C.S. Byington, M. J. Roemer, T. Galie, Prognostic enhancements to diagnostic systems for improved condition-based maintenance, Proceedings IEEE aerospace conference, vol.6(6), (2002).
[3] D. Jordan, S. Kurtz, Photovoltaic degradation rates-an analytical review, Progress in photovoltaics, 21(1), 12-29, (2013).
[4] P. Ribot, Y. Pencolé, M. Combacau, Functional prognostic architecture for the maintenance of complex systems, IFAC Proceedings Volumes, 42(8), 1450-1455, (2009).
[5] C.R. Osterwald, T. J. McMahon, History of accelerated and qualification testing of terrestrial photovoltaic modules: A literature review, Progress in photovoltaics, 17(1), 11-33, (2009).
[6] M. Vázquez, I. Rey-Stolle, Photovoltaic module reliability model based on field degradation studies, Progress in photovoltaics, 16(5), 419-433, (2008).
[7] R. F. Stapelberg, Handbook of reliability, availability, maintainability and safety in engineering design, Springer Science & Business Media, 99-105, (2009).
[8] R. Pan, T. Crispin, A hierarchical modeling approach to accelerated degradation testing data analysis: A case study, Quality and reliability engineering international, 27(2), 229-237, (2010).
[9] E. Monroe, R. Pan, Knowledge-based reliability assessments for time-varying climates, Quality and reliability engineering international, 25(1), 111-124, (2009).

[10] J. H. Wohlgemuth, D.W. Cunningham, P. Monus, J. Miller, A. Nguyen, Long term reliability of photovoltaic modules, IEEE 4th World Conference on Photovoltaic Energy Conference, vol. 2, 2050-2053, (2006)

[11] C. Notton, C. Cristofari, M. Mattei, P. Poggi, Modeling of a double-glass photovoltaic module using finite differences, Applied thermal engineering, 25(17-18), 2854-2877, (2005).

[12] A. Grous, Eléments d'analyse de la fiabilité et du contrôle de qualité : Statistiques appliquées par l'exemple, 113-199, Lavoisier, (2013).

[13] H. Akaike, A new look at statistical mode identification, IEEE Transactions on Automatic Control, 19(6), 716-723, (1974).

[14] International Energy Agency (IEA) Photovoltaic Power Systems Programme Task 13 Database, http://www.iea-pvps.org/, International Energy Agency, (2018).

[15] M. E. Şahin, H. İ. Okumuş, Physical Structure, Electrical Design, Mathematical Modeling and Simulation of Solar Cell Modules, Turkish Journal of Electromechanics & Energy 1(1), 5-12, (2016).

[16] X. Chen, Using the Akaike Information Criterion for selecting the field distribution in a reverberation chamber, IEEE Transactions Electromagnetic Compatibility, 55(4), 664-670, (2013).

Biographies

Mohamed Hassan Ali received the B.S degree in electronics, electrotechnical and automatic engineering in 2003 and the Master degree in microelectronics from Bordeaux University, France, in 2005. He obtained the Ph.D. degree in automatic and engineering in 2018 from University of Picardie Jules Verne, France. His research interest includes the characterization of PV cell, prognosis, and diagnosis of PV plants. He is also an Assistant Professor at the University of Djibouti since 2008.

E-mail: mohamed.hassan.ali@u-picardie.fr

Aamir Mehmood is serving as a Lecturer at the University of Engineering and Technology (Faisalabad Campus) Pakistan. He holds a Bachelor's degree in Mechanical Engineering from the University of Engineering and Technology and a Master's degree in Energy Systems Engineering from the National University of Sciences and Technology, Pakistan. He also has worked as a research associate at the City University of Hong Kong and is still engaged in collaborative research activities with national and international institutes in interested research domains. He also performs reviewing activities for reputed journals.

E-mail: aamir.mehmood08@gmail.com

Sofiane Haddad received the engineering degree in Electronics in June 2002, Magister degree in Electronics engineering (Signals and Systems) in April 2005 and Ph.D. in Electronic engineering, in April 2016, from Mohammed Seddik Ben Yahia University of Jijel, Algeria. Since 2008, he has been an Assistant Professor with the Electronics Engineering Department, MSBY University of Jijel, Algeria. His research is in the field of renewable energies and *PV* systems.

E-mail: sof_had@yahoo.fr