Degradation assessment of two silicon photovoltaic technologies under subtropical desert climate

Fatimazahra Oum'bark[1], Hicham Lotfi[2], Amin Bennouna[3], El Houssaine Ouacha[1]
[1]Laboratory of Metrology and Information Processing, Faculty of Sciences, Ibn Zohr University, Agadir, Morocco
[2]Higher School of Technology of Laâyoune-Ibn Zohr University, Laâyoune, Morocco
[3]Faculty of Sciences Semlalia, Cadi Ayyad University, Marrakech, Morocco

Article Info

Article history:

Received Jun 3, 2022
Revised Nov 4, 2022
Accepted Nov 10, 2022

Keywords:

ARIMA
CSD
Degradation rate
Holt-winters
Silicon PV technologies
STL

ABSTRACT

The prediction of performance of photovoltaic technologies is crucial, not only to improve the reliability and durability of these technologies but also to increase the confidence of investors and consumers in them. The accurate calculation of the degradation rate D_R (%) in real operating conditions under specific climatic stresses is, therefore, paramount. The present study provides a comparison of performance losses of two silicon PV technologies installed on the rooftop of the Higher School of Technology in Laâyoune-Morocco. The two systems are a polycristalline array (pc-Si: 1.82 kWp) and an amorphous array (a-Si: 1.55 KWp), which are grid connected. In the light of related performance gathered over three-year, the degradation rates of the two systems were estimated using four statistical methods under the open-source software R. The techniques engaged in this paper are: classical seasonal decomposition (CSD), holt-winters (HW), autoregressive integrated moving average (ARIMA), and seasonal and trend decomposition by LOESS (STL). The results obtained using those methods show that DR(%) varies between 0.39% and 0.99% for pc-Si and between 0.29% and 0.64% for a-Si. The analysis of degradation accuracy shows that STL and CSD techniques provide results with high accuracy than ARIMA and HW for the two systems. The present study adds to knowledge on PV degradation under the subtropical desert climate of Laâyoune.

Corresponding Author:

Fatimazahra Oum'bark
Laboratory of Metrology and Information Processing, Faculty of Sciences, Ibn Zohr University
Nouveau complexe universitaire, Agadir 80000, Morocco
Email: fatimazahra.oumbark125@gmail.com

NOMENCLATURE

a-Si: Amorphous Silicon
ARIMA: Autoregressive integrated moving average
c-Si: Crystalline Silicon
CdTe: Cadmium telluride
CIS: Copper indium-selenide
CSD: Classical seasonal decomposition
ES: Exponential smoothing
G_0: Solar irradiance under standard test conditions (W/m)
H_t: Total solar radiation arriving at the surface of PV panels (Wh/m^2)
HIT: Hetero-junction with intrinsic thin-layer
HW: Holt-winters
P^*_M: Effective peak power (W)
P_0: PV rated power (Wp)
P^*_{exp}: Experimental peak power (W)
pc-Si: Polycrystalline Silicon
PID: Potential-induced degradation
PR: Performance ratio (%)
PR_{DC}: DC- performance ratio (%)
PRt: Temperature corrected performance ratio (%)
Pt: Temperature-corrected power (W)
PV: Photovoltaic
PVUSA: Photovoltaics for utility scale applications
R_D: Degradation rates (%)

I: Current (A)
LID: Light-induced degradation
LLS: Linear least squares
LOESS: Locally weighted scatterplot smoothing
LR: Linear regression
mc-Si: Monocristalline silicon
MJ-Si: Multi-junction silicon
P: Power output (W)
STC: Standard test conditions
Ta: Ambient temperature (°C)
Tcell: temperature of the PV cell (°C)
V: Voltage (V)
Ya: Array yield (kWh/kWp)
Yf: Final yield (kWh/kWp)
YOY: Year-on-year
STL: Seasonal-trend decomposition by Loess
KToe: Kilotonne of oil equivalent

1. INTRODUCTION

The need of energy in the world rises every year. According to the International Energy Agency (IEA), the total energy consumption in the world in 2018 was 9 937 703 KToe. Giving the increasing prices of fossil energies and dramatic environmental issues brought about them, renewable energies stand as one of promising alternatives to ensure energy supplies along with environment protection. As any other technology; to entice more investors and consumers; the cost, the reliability and the lifetime must be attractive. Therefore, many studies were established in order to lower the costs and to guarantee high reliability, efficiency and durability of photovoltaic (PV) systems [1]–[4].

The loss of performance and degradation of PV systems are generated by external as well as internal factors. External ones are generally: temperature cycles [5], humidity, solar irradiation, mechanical stress, soiling, and snow. As for internal ones, the main cause is the imperfect production. Those factors result in different type of failure modes who are responsible not only for power loss but also for safety issue [6]. The prediction of the degradation rate D_R (%) of PV systems with high accuracy, during outdoor operation and under different climate conditions is still incompletely explored. The intention of this work is to enrich the pool of knowledge on PV degradation: using a case study of two silicon PV technology systems operating outside under climate conditions of Laâyoune City, in order to assess the performance degradation and determine which system is more suitable in such conditions.

Performance loss springs up at different level: cell, module, array and system with various factors and degradation mechanisms at each level [7]. The paper exhibited different failure modes and showed their related impacts on the performance of PV module, as well as defining the risk priority number "RPN" for each defect who describes which one affect the system performance more [8]. This study showed also that hot-spot and encapsulant delamination, back sheet delamination, corrosion in solder bond fatigue are crucial failures connected with the security issue with lower RPN number <50 [8]. In the literature, many methods are used in order to determine the performance loss of PV systems, which can be classified into two types: analytical models and statistical methods. The first ones are generated from the physical/chemical theories of a specific failure, by representing the mechanism involved in complex physical/chemical processes [9]. Statistical methods generally used are namely: simple linear regression (SLR) classical seasonal decomposition (CSD) holt-winters (HW) auto-regressive integrated moving average (ARIMA) and locally weighted scatterplot smoothing method (LOESS). The various choices of the measuring equipment, the data qualification, filtering criteria, the performance metric and the statistical method of estimation of the trend, spin off different results with varying uncertainty [7].

The estimation of the degradation rate D_R (%) of peak power of two grid-connected PV systems of two different technology having the same capacity of 24 kWp was conducted by using linear least square fitting method [10]. Dag and Buker [10] reveled that the thin-film technology (HiT) shows lower degradation rate with about 0.1% than the poly-crystalline (pc-Si) based technology within the range of 0.67% to 0.83%, respectively, after two and half year out-dour exposure under the semi-arid weather of Anatolia-Turkey. Another study from Solís-Alemán *et al.* [11] was interested in exploring the linearity of the degradation rate of various thin film technologies in Jaén, Southern Spain. In this paper two methods were applied: classical seasonal decomposition (CSD) and year-on year (YOY) in order to discover the path of degradation of two PV field PVGCS #1(a-Si) and PVGCS #2 (a-Si/μc-Si) of 60 Wp and 110 Wp capacity, respectively. Four PV modules of four technologies were also studied -a-Si, a-Si:H/ μc-Si:H, cadmium telluride (CdTe) and copper indium gallium selenide (CIGS)- under outside conditions. According to the first method, the degradation rates were around 1.32%, 1.22%, 1.50% for a-Si, a-Si/μc-Si fields and a-Si module respectively [11]. The a-Si/μc-Si PV module shows a lower power loss (~0.6%/year). The CdTe PV module, likewise, has a degradation rate who is nearly negligible according to CSD, while the YOY indicates that such parameter lies nearby 0.7%/year. Whereas the CIGS PV module exhibits an interesting improvement at a rate around−0.92%/year, as presented by the same study [11]. An example for utility scale PV system was explored by the study [12], in which, a system of 1MWp installed in a tropical semi-arid climate in Telangana State- India was investigated by applying LLS, CSD, HW and STL to the time series of performance ratio collected over four years of operation, the degradation rate found was respectively 0.27 ± 0.22%/year, 0.32 ± 0.11%/year, 0.50 ± 0.22%/year, and 0.27 ± 0.15%/year, according to the study.

Other studies were interested in analyzing the degradation rate caused by specific failures. The paper reveals that after three years of outdoor exposure, under semi-arid climate in Bengurir-Morocco; the power degradation rate reached 4.57%/year in the modules with breakage and cracks [13]. After evaluating 144 failure-survey-data collected from 18 countries, the most dominant defects encountered according to study [14] were: cell crack, potential induced degradation by shunts, defect bypass diodes and discoloring of the pottant. The mean degradation rates in moderate climate for cell crack, PIDs and discoloring of pottant were 5%, 16%, and 1% respectively. Another study underlines the main PV defects occurring after a longer-term operation of 22 years under the prevailing weather in Seville-Spain. Lillo-Sánchez *et al.* [15] found that the important aspects of degradation occurred were: severe browning, milky pattern and oxidation of the metallization grid. That results in a degradation rate of the mean peak power of 1.4%/years. An attempt to enhance, more globally, the understanding of PV performance and degradation was made by the study [16], by providing a map of degradation mechanisms and degradation rate for mono-crystalline PV module. The map can be considered a guide for localizing zones with high climate stress. However, the development of a global map of the degradation for each PV technology under diverse operating and climatic conditions needs further contributions. This paper provides a case study of two grid-connected PV technologies operating outdoors under subtropical climate conditions.

In light of this information, the calculation of the degradation rate DR (%) is important to lower the performance uncertainty and predict their evolution with high accuracy. Firstly, this paper will present the two systems under consideration as well as the four statistical techniques used (section 2). Secondly, this study will evaluate the performance loss rate of the two systems using the statistical methods (Section 3) and provide a comparison between the results given by these techniques and their accuracy. Finally, A comparison of results in this work with previous papers will also be mentioned. The present work is dedicated to exploring how the two PV systems perform under the prevailing weather in Laâyoune City, and how their performances degrade using different statistical techniques under R software.

2. MATERIALS AND METHOD

2.1. Materials description

The two PV systems under the scope of the study, were installed in March 2018 as part of the “Propre.ma” project; who aims to develop a map of the productivity of different PV technologies over the Moroccan Kingdom; in the north-west of the ESTL, University IBN Zohr (latitude 27°07'50.4 "north and longitude 13°08'18.1" west) under semi-arid climate conditions. The installation is fundamentally formed by three PV technologies Poly-crystalline p-Si (1.82 kWp) and Mono-crystalline m-Si (2 kWp) and Amorphous silicon thin film technology a-Si (1.55 kWp) who are linked together in order to form a grid connected system of total power of 5.365kWp. A previous work was interested in determining the performance of these two silicon technologies in addition to mc-Si array [17]. In this study, only the pc-Si and a-Si will be considered.

The amorphous PV system comprises ten amorphous silicon thin-film panels linked in series of 155Wp each. As for the poly-crystalline PV system, it contains seven panels, each with power of 260 W linked also in series. The Table 1 below represents the technical specification of the two types of modules, as shown in the panel’s nameplate of each technology:

Table 1. Technical specification of PV modules

Trade mark	Nexpower	Solarworld
Model	NT-155AF	Sunmodule plus SW 260 poly
Solar cell	Thin film, Amorphous Si	Polycrystalline
Maximum power At STC (Pm)	155 W	260 W
Maximum power point voltage (Vmp)	65.9 V	31.40 V
Maximum power current (Imp)	2.43 A	8.37 A
Open circuit voltage (Voc)	85.5 V	34.40 V
Short circuit current (Isc)	2.56 A	8.94 A
Length	1.4 m	1.675 m
Width	1 m	1 m
Weight	19.5 Kg	18Kg

2.2. Performance metrics

Performance metrics are generally used in order to readily compare different PV systems in different climates conditions. In this paper, we have based the estimation of performance loss D_R (%) on normalized performance metric, which is array yield (Y_A). Monthly data are recorded over a monitoring period of three years from January 2018 to December 2020, in order to establish time series of Y_A. The expressions of performance parameters are based on definitions standardized by IEC 61724 [18].

2.2.1. Reference Yield (Yr)

The reference yield Yr reflects the number of hours during which the solar radiation would need to be at reference irradiance levels to contribute the same incident energy. The array yield Yr has unit of hour (h). This yield can be calculated by dividing the total solar in-plane irradiation Ht (KWh/m2) by the reference in-plane irradiance G0, (1 KW/m2), as given by the following (1).

$$Yr = \frac{\mathrm{Ht}}{\mathrm{G0}} \tag{1}$$

2.2.2. Array yield (Y_A)

The array yield Y_A is the daily array energy output $E_{A,d}$ per kW of installed PV array P_0. This yield represents the number of hours per day that the array would need to operate at its rated output power P_0 to contribute the same daily array energy to the system as was monitored [12]. It is calculated by using the expression:

$$Y_A = \frac{EA,d}{P0} \tag{2}$$

2.3. Methodology of Statistical methods

In order to evaluate the annual degradation rate of the two silicon PV technology under study (pc-Si and a-Si), four statistical methods are applied to the monthly time series of Array Yield Y_A of each technology. The classical seasonal decomposition (CSD), holt winters exponential smoothing (HW), autoregressive integrated moving average (ARIMA) and seasonal and trend decomposition using LOESS (STL) techniques were implemented to calculate the degradation rate (D_R in units of %/ year) from the trend of PV module performance time series, using the slope of such a trend given by applying linear regression [7]. The simulation was done using R, an open-source Software. The annual degradation rate of PV grid-connected system can be given by (3): where a is the slope of the trend.

$$D_R(\%) = a * 12 \tag{3}$$

2.3.1. Classical seasonal decomposition (CSD)

In the CSD method, the time series is decomposed to three elements: the trend, seasonal and remainder random element. The trend is a result of the application of a moving average centered on two steps. Giving a moving average of 2k, where k is the order of the moving average, the centered average at time t which represents the trend (Tt) at time t, which is given by (4) [7]:

$$T_t = \frac{1}{2}\left(\frac{1}{k}\sum_{i=t-m}^{t+m-1} Y_i + \frac{1}{k}\sum_{i=t-m+1}^{t+m} Y_i\right) \tag{4}$$

where: m=k/2 is defined as half the width of a moving average [9].

As for the seasonal element, it is given by subtracting the trend from the initial time series data, according to the (5) [9]:

$$S_t = Y_t - T_t \tag{5}$$

the degradation rate D_R (%) is, then, calculated from the trend element by using linear regression. The D_R (%) is calculated by multiplying the slope 'a' of the linear regression curve of the extracted trend by 12 as presented in (3) [9].

2.3.2. Holt-winters model (HW)

The Holt-winters (HW) technique is derived from a triple exponential smoothing method. This model-based method is applied to the time series and takes into account seasonal variations in addition to trends. The model establishes the trend, seasonal and residuals components by the application of centered moving average, through the minimization of the squared one-step ahead error [7]. The HW method for PV systems follows the general additive model as shown in (6) [9], [19]:

$$y_{t+1|t} = l_t + b_t + S_{t-S+1} \tag{6}$$

where l_t is the level component, b_t the slope component and S_{t-s+1} the relevant seasonal component, s the seasonal period, their expressions are given in (7)-(9) [9]:

$$l_t = A(y_t - S_{t-S}) + (1 - A)(l_{t-1} + b_{t-1}) \tag{7}$$

$$b_t = B(l_t - l_{t-1}) + (1 - B)b_{t-1} \tag{8}$$

$$s_t = C(y_t - l_{t-1} - b_{t-1}) + (1 - C)s_{t-S} \tag{9}$$

where A, B and C values are within [0,1] interval.

2.3.3. Autoregressive integrated moving average (ARIMA)

ARIMA is a model, which holds various methods in a multiplicative way, and can be abbreviated as ARIMA (p, d, q) (P, D, Q). Where p is the auto-regressive, d the differencing, and q the moving average order. As for P, D, and Q, they represent the seasonal autoregressive, the seasonal differencing, and the seasonal moving average order, respectively. [9] One of the most important advantages of the model is its flexibility to deal with seasonal fluctuations, errors, outliers, and level shifts, in a suitable way [9]. The general model of ARIMA can be given by the following expression (10).

$$\phi(T)\phi_S(T^S)\nabla^d\nabla_S^D y_t = \theta(T)\theta_S(T^S)e_t \tag{10}$$

Here T represents the delay operator, $\phi(T) = \left(1 - \phi_1 T - .. - \phi_p T^p\right)$represents an autoregressive polynomial in T of degree p, $\phi(T^s)$ is an autoregressive polynomial in Ts of degree PS. $\theta(T)$ is a moving average polynomial in T of degree q, $\theta_s(T^s)$ is a moving average polynomial of degree Qs in Ts. The operator $\nabla^d = (1 - \mathrm{T})^{\mathrm{d}}$ is a non-seasonal differencing operator, and ∇_S^D is a seasonal differencing operator and captures non-stationarity in the corresponding locations in consecutive periods [9].

2.3.4. Seasonal–trend decomposition using LOESS (STL)

STL decomposition is a non-parametric method, which estimates non-linear relationship by using a locally weighted regression instead of centered moving average to extract the trend. Thus, the method is more robust and less influenced by missing values and outliers [9]. Furthermore, it is flexible in defining the amounts of fluctuations in the trend and seasonal components. In addition, it has the flexibility in specifying the number of observations per cycle of seasonal component to any integer greater than one [20]. As CDS method, STL model aims to decompose the time series to three components as define in (11).

$$Y_t = T_t + S_t + R_t \quad t=1,2\ldots\ldots, n \tag{11}$$

Where T_t, S_t and R_t are the trend, the seasonal and the residual components, respectively [9].

3. RESULTS AND DISCUSSION

3.1. Variation and seasonality of parameter metric

Figure 1 and Figure 2 illustrate three-year time series of array yield (Y_A) monthly average values, of the two PV technologies under study, from January 2018 to December 2020. A preliminary analysis of the 36 data of each technology shows that the two arrays (pc-Si and a-Si) manifest a clear decreasing trend and a seasonal behavior.

Figure 1 represents the pc-Si array yield variations over the 36 months from January 2018 to December 2020. The degradation of the pc-Si array yield is clearly shown by the decreasing trend of the curve. As for the variation due to the seasonality, the improvement of pc-Si performance is observed during the winter's months. The high enhancement of pc-Si performance during the coldest months is due to the lowest module's temperature, under the lower ambient temperature [21]. While during the warmest season the pc-Si efficiency is generally lower [22], [23]. The fluctuations of a-Si array yield (Y_A) during the monitoring period are illustrated figure 2. As reported in many literature studies, the a-Si performance is influenced by Steabler Wronski effect [22] which explains the remarkable degradation of the array yield during the first year.

As reported by many literature studies, a-Si array reaches its peak of performance in high temperature condition due to the thermal annealing cycles; which helps recover some of performance loosed because of light induced degradation [24].

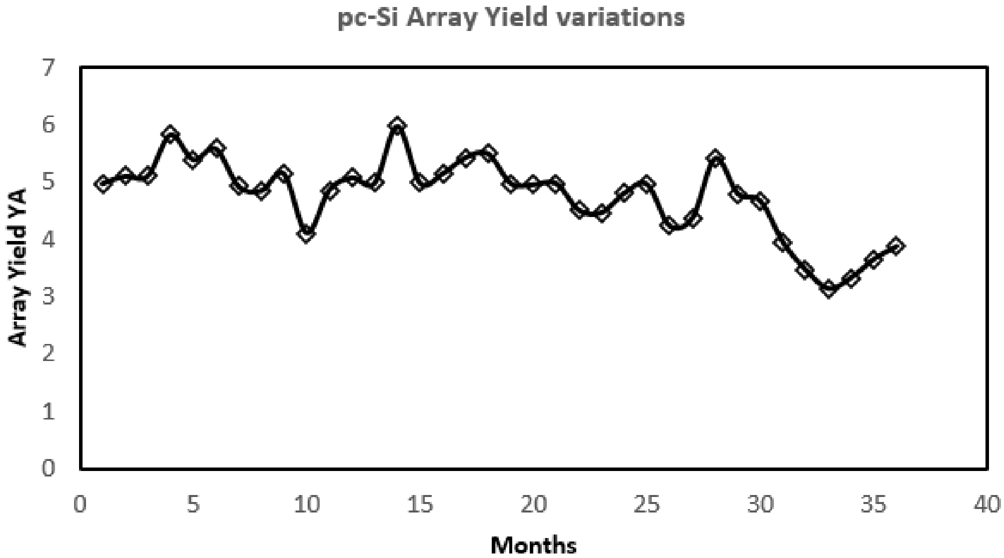

Figure 1. Array yield variations of pc-Si

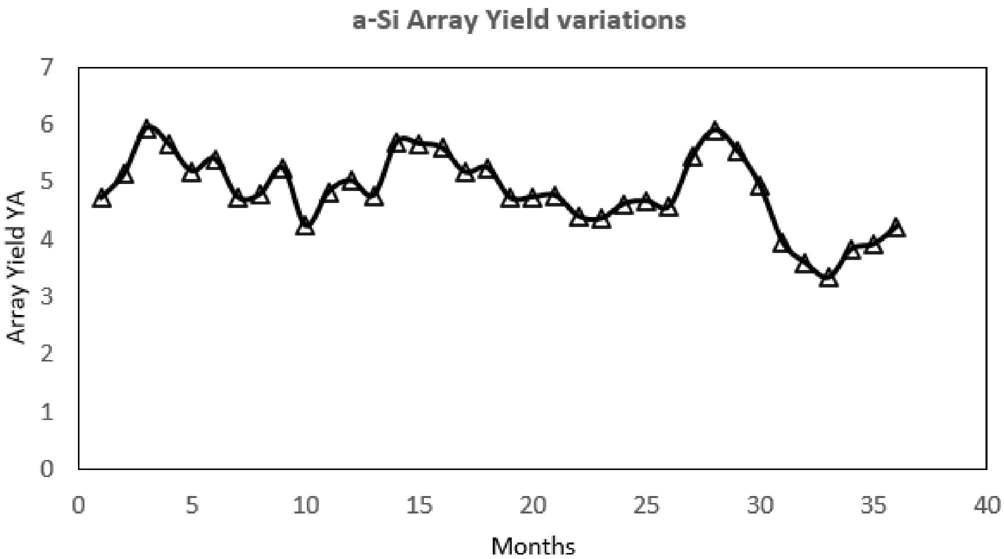

Figure 2. Array yield variations of a-Si

3.2. Degradation rates of array yield using statistical methods

3.2.1. Array yields and classical seasonal decomposition method (CSD)

The classical and seasonal decomposition is one of the most employed statistical techniques to estimate the performance loss. Using the additive model of this method, we can extract the trend, the seasonal and the irregular components from the initial time series of Y_A the trend component helps get a fast idea of the performance degradation of the system [4]. Figures 3 and 4 illustrate the results found using the CSD technique under R:

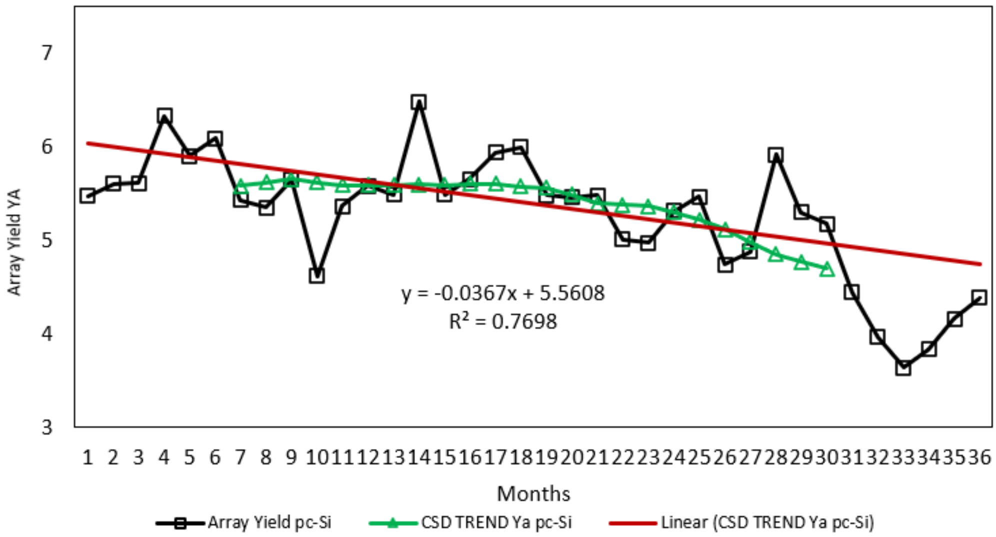

Figure 3. Y_A and CSD method for pc-Si

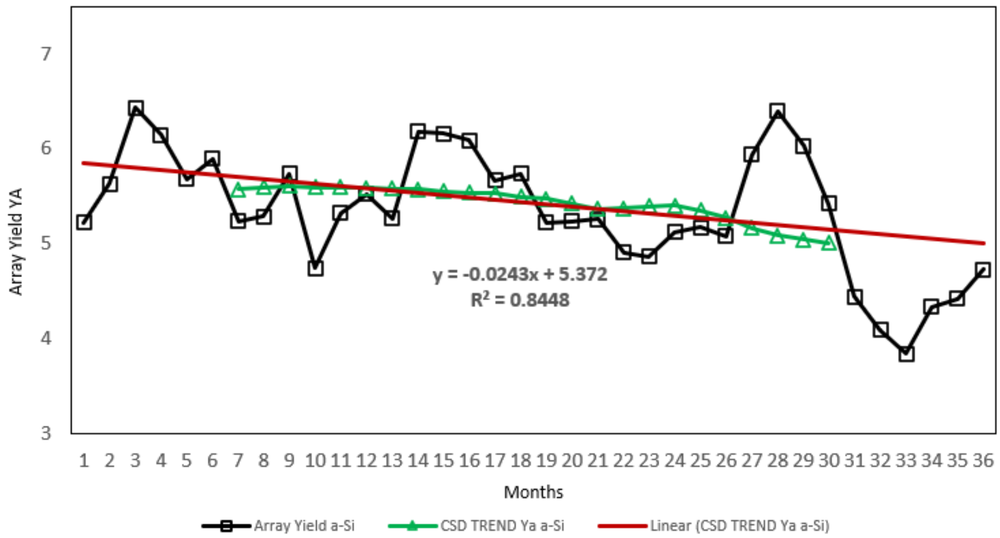

Figure 4. Y_A and CSD method for a-Si

The CSD method was applied to the time series of Y_A, in order to quantify the degradation observed from the trend and described in section 3-1. As shown in Figures 3 and, according to this method the degradation rate for pc-Si system is found to be 0.44 %. While for a-Si the degradation rate is around 0.29%.

3.2.2. Array yield and holt-winters model (HW)

Although being less employed in PV degradation assessment, Holt-Winters method is also used to predict PV performance series [25].The HW model can be either additive or multiplicative, depending on the seasonal variations. As the seasonal fluctuations of PV systems are practically constant over the series, the additive model of Holt-winters algorithm is used in order to evaluate the degradation rates of the two PV systems [4]. The application of the linear regression to the HW series results in the determination of the slopes of the trends, which will be used according to (3) to calculate the performance loss rates. Figures 5 and 6 represent results obtained after the application of Holt-Winter algorithm to the time series of the Array Yield (Y_A) for the two technologies.

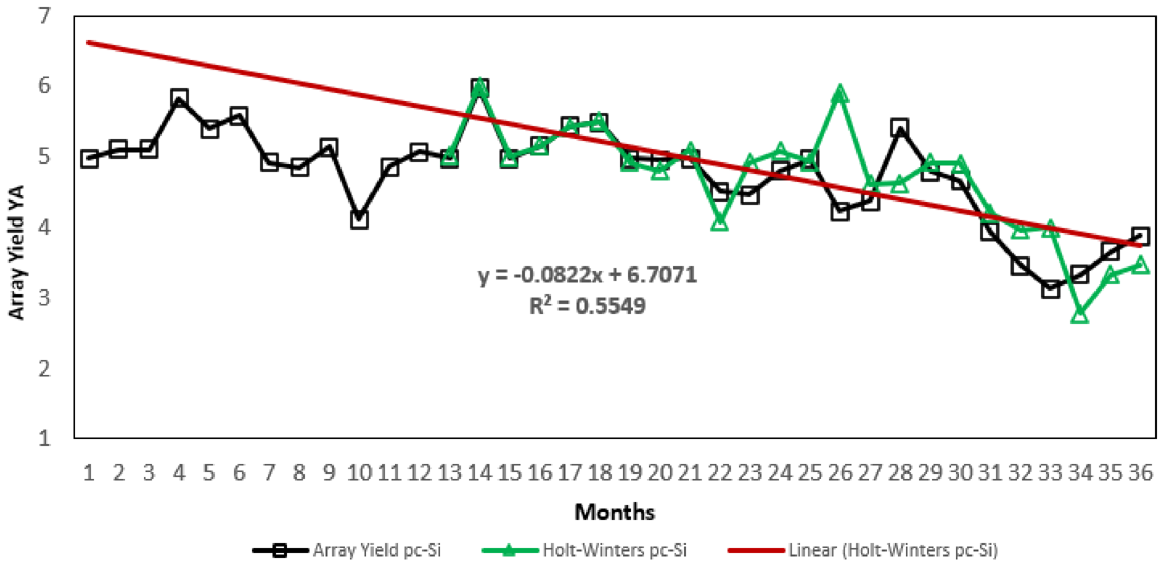

Figure 1. Y_A and HW model for pc-Si

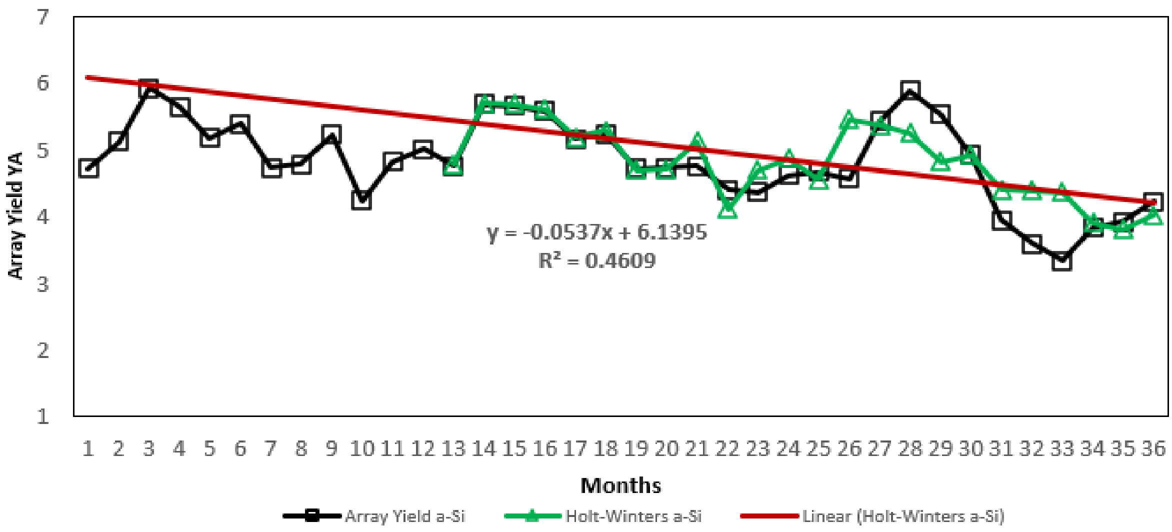

Figure 6. Y_A and HW model for a-Si

After the optimization of the Holt-Winters model under R, the parameters values of the model for pc-Si are α=0.11, β=0.49, γ= 0.16. As for a-Si array, these parameters are α=0.03, β=1, γ=1. The degradation rate DR (%) reaches for pc-Si system 0.99%. As for a-Si field, the YA depreciates at rate of 0.64%.

3.2.3. Array yield and auto regressive integrated moving average method (ARIMA)

ARIMA is also one of the most popular statistical methods, which is used; for PV systems; not only to assess the degradation of performance, but also to forecast the variation of performances in the future [26], [27]. Here, we are interested in the assessment of the degradation of the array yields of the two technologies under study. Again, the linear regression is called to evaluation the rates of the depreciation of performances. Figures 7 and 8 show results of application of the ARIMA method to the time series of Y_A of the two fields under study.

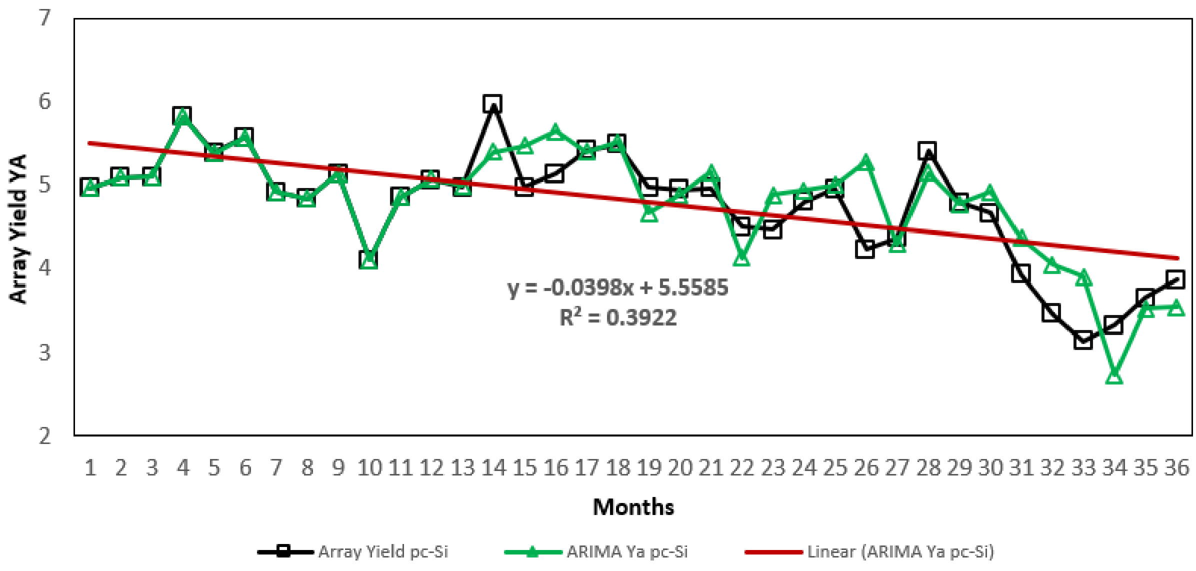

Figure 7. Y_A variations and ARIMA model for pc-Si

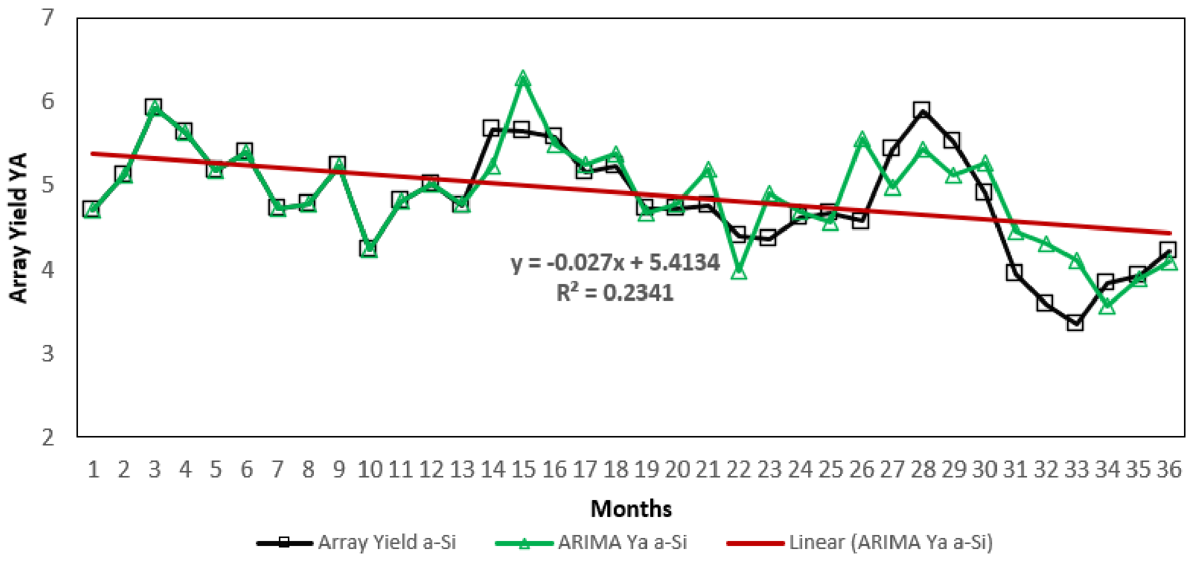

Figure 8. Y_A variations and ARIMA model for a-Si

After seeking the best ARIMA model that fits the times series under R, the parameters values for the model are ARIMA (2,1,0)(1,1,0)12 for pc-Si; while for a-Si field the parameters are ARIMA(0,1,2)(0,1,0)12. The degradation rate is around 0.48% for the pc-Si field; while for a-Si system it is about 0.32%.

3.2.4. Array yield and seasonal-trend decomposition using LOESS (STL)

The seasonal-Tend decomposition using LOESS is a powerful and flexible statistical method usually used in PV degradation assessment. The trend of the STL decomposition is explored in order to find out the slopes of the decreasing performance metrics of the two PV arrays. The application of the linear regression to the STL trends comes up with the estimation of the decline of array yields over time of the two PV systems. The Figures 9 and 10 exhibits the results of the application of STL method to the Y_A time series of the two technologies. For pc-Si the degradation rate is found to be 0.39%, while for a-Si the D_R (%) is about 0,29 %.

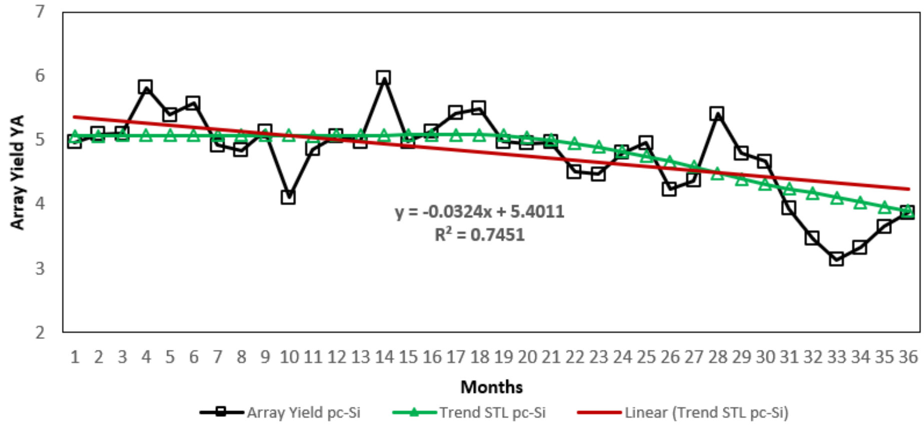

Figure 9. Y_A variations and trend of STL decomposition for pc-Si

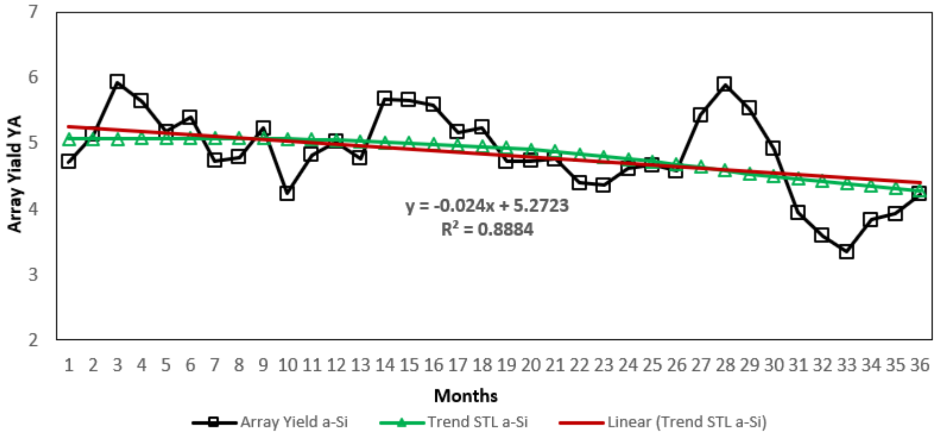

Figure 10. Y_A variations and trend of STL decomposition for a-Si

3.3. Discussion of results

Table 2 summarizes the annual degradation rates D_R (%) for the four methods, as well as the associated uncertainties and the coefficients of determination (R^2). The different results of degradation rate D_R (%) acquired show that the degradation of PV performance depends on the statistical method used in addition to PV technology under consideration. Other parameters that affect the degradation rate are climate conditions [28], operating topologies, and the cumulative history of exposure to meteorological conditions [7].

Table 2. Degradation rates DR (%) of the two technologies under study

Technology	Parameter	CSD	Holt-Winters	ARIMA	STL
pc-Si	DR (%)	0.44 ± 0.05%	0.99 ± 0.19%	0.48 ± 0.10%	0.39±0.04%
	R2	0.77	0.56	0.39	0.75
a-Si	DR (%)	0.29 ±0.03%	0.64 ± 0.15%	0.32 ± 0.10%	0.29±0.02%
	R2	0.85	0.46	0.23	0.89

In one side, the corresponding uncertainty to each degradation rate obtained from the application of the four methods give us the accuracy of each model. For both of pc-Si and a-Si arrays, the STL method provides the lowest D_R (%) with the best accuracy, 0.04% for pc-Si and 0.02% for a-Si. Here, STL model excels the CSD technique which comes up with low degradation rates with larger uncertainties: 0.05% for pc-Si and 0.03% for a-Si. While the highest D_R (%) was given by HW model with the worst accuracy, 0.19% for pc-Si and 0.15% for a-Si. In the case of ARIMA method, it returns intermediate D_R (%) for the two PV arrays with intermediate uncertainty of 0.10% for both pc-Si and a-Si fields.

On the other side, values of coefficient of determination R^2 helps us to assess how well the linear regression model, used to extract the trend coefficient, fits the data generated by each technique. More the value of R^2 is close to '1' more the degradation of the performance metric modeled is approximately linear. For the four techniques used in this work, the maximal values of R^2 are obtained by the application of STL method (0.75 for pc-Si and 0.89 for a-Si). Here again, STL outperforms CSD process which provides an R^2 of 0.77 for pc-Si and 0.85 for a-Si. While intermediate and low values of the same coefficient R2 are presented by HW model (0.55 for pc-Si and 0.46 for a-Si) and ARIMA (0.39 for pc-Si and 0.23 for a-Si) models; respectively. This questions the linear approach conventionally adopted to deal with the degradation rate of different PV technologies [29].

As previously discussed, many factors influence the loss of performance of PV system. Table 3 (see Appendix) shows the degradation rates of different PV systems obtained by previous studies [10]-[12], [15], [30]–[33] using Several statistical methods, during various exposure periods and under dissimilar climate conditions. According to Köppen-Geiger climate classification [34], the weather in Laayoune City is considered to be a subtropical desert climate. A comparative study was carried out using results of nine previous works, which contain several PV plants. Only 17 systems are explored, which are composed of nine pc-Si and eight a-Si arrays. In one hand, various statistical methods are used to estimate the PV degradation rates. According to Table 3; LR/LLS and CSD are the most popular techniques to estimate the rate of performance losses D_R (%) (six studies for LR/LLS and four studies for CSD). On the other hand, high-performance losses can be found in composite climate (3.96% for a-Si), followed by desert and semi-arid climate (0.99% for pc-Si and 1.99% for a-Si). While low degradation rates are observed in semi-arid (0.2% for a-Si) and temperate climate (0.21% for pc-Si). If we do not consider the composite climate and look over the degradation rates of all parameter metrics; the loss of performance of a-Si fields passes by a minimum rate of 0.2% and a maximum of 1.99% with an average rate of 1.32%. As for pc-Si arrays the degradation rates have a minimum of 0.21% and a maximum of 0.99% with an average value of 0.61%. The comparative analysis conducted reveals that the degradation rates found in this work are in agreement with values mentioned in previous works.

4. CONCLUSION

In this paper, degradation assessment of the two silicon PV technologies (pc-Si and a-Si) over three years of outdoor-exposure and under climate conditions of Laâyoune City has been conducted. The four statistical methods applied to Y_A time series, using R software are: classical seasonal decomposition (CSD), holt-winters (HW), auto regressive integrated moving average (ARIMA) and Seasonal-trend decomposition using LOESS (STL). The main results and findings are recapitulated: i) the two technologies present a seasonal behavior; ii) the annual degradation rate for pc-Si is found to be around 0.44%, 0.99 %, 0.48% and 0.39 %, using CSD, HW, ARIMA, and STL respectively with an average rate of 0.58%/Year; iii) while the array yield of a-Si degrades at rate of 0.29%, 0.64%, 0.32% and 0.29%, using CSD, HW, ARIMA, and STL respectively with an average rate of 0.39%/year; iv) Si array's performance metric degrades less than that of pc-Si under the meteorological conditions of Laâyoune; and v) the four statistical methods have shown that the two technologies exhibit an annual degradation rate less than 1%; with different uncertainties. The STL method excels the three other techniques in terms of accuracy (±0.04% for pc-Si and ±0.02% for a-Si) while the highest uncertainty is obtained using the HW model (±0.19% for pc-Si and ±0.15% for a-Si). vi) Results and findings of the present work are in agreement with results mentioned in previous works.

APPENDIX

Table 3. Degradation rates D_R(%) of PV systems from previous studies

Location and Climate (Köppen - Classification)	Technology of Pv Module	Duration (Years)	Parameter Metric	Methodology	D_R (%)	Reference
AIST Tsukuba	pc-Si	3	$PR_{T=25}$	LR	-0.31	[30]
Japan-	pc-Si				-0.51	
temperate climate	pc-Si				-0.55	
	pc-Si				-0.46	
	pc-Si				-0.21	
	pc-Si				-0.34	
	sc-Si				-0.76	
	sc-Si				-0.73	
	sc-Si				-0.96	
	a-Si:H/c-Si				-0.27	
	a-Si				-1.43	
	a-Si				-1.38	
	CIGS				0.16	
	CIGS				0.23	

Table 3. Degradation rates D_R(%) of PV systems from previous studies *(continue)*

Location and Climate (Köppen - Classification)	Technology of Pv Module	Duration (Years)	Parameter Metric	Methodology	D_R (%)	Reference
Tucson, Arizona, USA Semi-Arid	a-Si	3	Yf	Bayesian statistical analysis	-0.20	[31]
Saida, Algeria Desert and semi arid	mc-Si (Multicristalin)	3	PR	LLS	-0.83	[32]
			P*M		-0.74	
	c-Si (mono-cristallin)		PR	LLS	-0.79	
			P*M		-0.58	
	HiT		PR	LLS	-1.92	
			P*M		-1.53	
University of Cyprus in Nicosia, Germany-Desert and semi arid	pc-Si	3	PR	CSD	-0.99	[35]
				ARIMA	-0.92	
	a-Si	3	PR	CSD	-1.87	
				ARIMA	-1.99	
Telangana, India Tropical semi-arid	mc-Si	4	PR	LLS	-0.27	[12]
				CSD	-0.32	
				HW	-0.50	
				STL	-0.27	
Konya Anatolia, Turkey-Semi arid	pc-Si	2.5	P*M	LLS	-0.83	[10]
	HIT				-0.67	
Jaén (Spain) -Temperate	a-Si	5.5	P*exp	CSD	-1.22	[11]
				YOY	-1.32	
			PRDC	CSD	-1.16	
				YOY	-1.40	
			PRDC, STC	CSD	-1.25	
				YOY	-1.27	
India- Composite Climate Condition	a-si_1	3	PR	LR	-3.76	[30]
				CSD	-3.96	
				LOESS	-2.83	
	a-si_2			LR	-3.67	
				CSD	-3.36	
				LOESS	-2.11	
	a-si_3			LR	-3.73	
				CSD	-3.12	
				LOESS	-2.32	
	HIT-1			LR	-0.63	
				CSD	-0.48	
				LOESS	-1.33	
	HIT-2			LR	-0.26	
				CSD	-0.24	
				LOESS	-1.84	
	HIT-3			LR	-0.38	
				CSD	-0.34	
				LOESS	-1.87	
	mc-Si-1			LR	-5.12	
				CSD	-5.04	
				LOESS	-2.70	
	mc-Si-2			LR	-4.09	
				CSD	-3.84	
				LOESS	-2.40	
	mc-Si-3			LR	-4.29	
				CSD	-4.32	
				LOESS	-2.32	
Seville, (Spain)-Temporate	mc-Si	22	Pmax	LR	-1.40	[15]

ACKNOWLEDGEMENTS

This work is part of the 'Propre.Ma' project, which has been sponsored by IRESEN (Morocco) since March 2018 in Laâyoune city. In the name of all the rest of the consortium members, the authors would like to thank IRESEN board and scientific committee for financing this through the INNO'PV program as well as its general manager, Badr IKKEN, and the rest of the staff for their daily efforts. Authors are grateful to the members of the 'Propre.Ma' consortium who are essential for territorial extension the project.

REFERENCES

[1] H. F. Hashim, M. M. Kareem, W. K. Al-Azzawi, and A. H. Ali, "Improving the performance of photovoltaic module during partial shading using ANN," *Int. J. Power Electron. Drive Syst.*, vol. 12, no. 4, p. 2435, Dec. 2021, doi: 10.11591/ijpeds.v12.i4.pp2435-2442.

[2] M. N. Kamarudin, S. M. Rozali, and M. S. Jamri, "Active cooling photovoltaic with iot facility," *Int. J. Power Electron. Drive Syst.*, vol. 12, no. 3, pp. 1494–1504, 2021, doi: 10.11591/ijpeds.v12.i3.pp1494-1504.

[3] E. Z. Ahmad *et al.*, "Recent advances in passive cooling methods for photovoltaic performance enhancement," *Int. J. Electr. Comput. Eng.*, vol. 11, no. 1, p. 146, Feb. 2021, doi: 10.11591/ijece.v11i1.pp146-154.

[4] H. Attia and K. Hossin, "Hybrid technique for an efficient PV system through intelligent MPPT and water cooling process," *Int. J. Power Electron. Drive Syst.*, vol. 11, no. 4, p. 1835, Dec. 2020, doi: 10.11591/ijpeds.v11.i4.pp1835-1843.

[5] J. C. Ogbulezie, A. O. Njok, M. K. Panjwani, and S. K. Panjwani, "The impact of high temperature and irradiance source on the efficiency of polycrystalline photovoltaic panel in a controlled environment," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 4, pp. 3942–3947, 2020, doi: 10.11591/ijece.v10i4.pp3942-3947.

[6] M. Koentges *et al.*, "Performance and Reliability of Photovoltaic Systems, Subtask 3.2: Review of Failures of Photovoltaic Modules," 2014.

[7] A. Phinikarides, N. Kindyni, G. Makrides, and G. E. Georghiou, "Review of photovoltaic degradation rate methodologies," *Renew. Sustain. Energy Rev.*, vol. 40, pp. 143–152, Dec. 2014, doi: 10.1016/j.rser.2014.07.155.

[8] P. Rajput, M. Malvoni, N. M. Kumar, O. S. Sastry, and G. N. Tiwari, "Risk priority number for understanding the severity of photovoltaic failure modes and their impacts on performance degradation," *Case Stud. Therm. Eng.*, vol. 16, p. 100563, Dec. 2019, doi: 10.1016/j.csite.2019.100563.

[9] S. Lindig, I. Kaaya, K.-A. Weiss, D. Moser, and M. Topic, "Review of Statistical and Analytical Degradation Models for Photovoltaic Modules and Systems as Well as Related Improvements," *IEEE J. Photovoltaics*, vol. 8, no. 6, pp. 1773–1786, Nov. 2018, doi: 10.1109/JPHOTOV.2018.2870532.

[10] H. I. Dag and M. S. Buker, "Performance evaluation and degradation assessment of crystalline silicon based photovoltaic rooftop technologies under outdoor conditions," *Renew. Energy*, vol. 156, pp. 1292–1300, Aug. 2020, doi: 10.1016/j.renene.2019.11.141.

[11] E. M. Solís-Alemán, J. de la Casa, I. Romero-Fiances, J. P. Silva, and G. Nofuentes, "A study on the degradation rates and the linearity of the performance decline of various thin film PV technologies," *Sol. Energy*, vol. 188, pp. 813–824, Aug. 2019, doi: 10.1016/j.solener.2019.06.067.

[12] M. Malvoni, N. M. Kumar, S. S. Chopra, and N. Hatziargyriou, "Performance and degradation assessment of large-scale grid-connected solar photovoltaic power plant in tropical semi-arid environment of India," *Sol. Energy*, vol. 203, pp. 101–113, Jun. 2020, doi: 10.1016/j.solener.2020.04.011.

[13] C. Hajjaj *et al.*, "Degradation and performance analysis of a monocrystalline PV system without EVA encapsulating in semi-arid climate," *Heliyon*, vol. 6, no. 6, p. e04079, Jun. 2020, doi: 10.1016/j.heliyon.2020.e04079.

[14] K. A. B. Marc Köntges, Sascha Altmann, Tobias Heimberg, Ulrike Jahn, "Mean degradation rates in PV systems for various kinds of PV module failures," *32nd Eur. Photovolt. Sol. Energy Conf. Exhib.*, no. May, p. 1438, 2016, [Online]. Available: http://www.isfh.de/institut_solarforschung/files/5dp.1.2_koentges_paper.pdf

[15] L. Lillo-Sánchez, G. López-Lara, J. Vera-Medina, E. Pérez-Aparicio, and I. Lillo-Bravo, "Degradation analysis of photovoltaic modules after operating for 22 years. A case study with comparisons," *Sol. Energy*, vol. 222, pp. 84–94, Jul. 2021, doi: 10.1016/j.solener.2021.04.026.

[16] J. Ascencio-Vásquez, I. Kaaya, K. Brecl, K.-A. Weiss, and M. Topič, "Global Climate Data Processing and Mapping of Degradation Mechanisms and Degradation Rates of PV Modules," *Energies*, vol. 12, no. 24, p. 4749, Dec. 2019, doi: 10.3390/en12244749.

[17] H. Lotfi, L. Boughamrane, and D. Izbaim, "Performance of different silicon PV technologies installed in Laâyoune-Morocco," */ Appl. J. Envir. Eng. Sci*, vol. 6, pp. 160–172, 2020.

[18] Commission IEC, "Photovoltaic system performance monitoring-guidelines for measurement, data exchange and analysis - Part 1: Monitoring," *Int Stand IEC.* pp. 1–10, 2017.

[19] C. C. Holt, "Forecasting seasonals and trends by exponentially weighted moving averages," *Int. J. Forecast.*, vol. 20, no. 1, pp. 5–10, Jan. 2004, doi: 10.1016/j.ijforecast.2003.09.015.

[20] R. B. Cleveland, W. S. Cleveland, J. E. McRae, and I. Terpenning, "STL: A Seasonal-Trend Decomposition Procedure Based on Loess (with Discussion)," *J. Off. Stat.*, vol. 6, no. 1, pp. 3–73, 1990, [Online]. Available: http://cs.wellesley.edu/~cs315/Papers/stl statistical model.pdf

[21] G. Makrides, B. Zinsser, M. Schubert, and G. E. Georghiou, "Performance loss rate of twelve photovoltaic technologies under field conditions using statistical techniques," *Sol. Energy*, vol. 103, pp. 28–42, May 2014, doi: 10.1016/j.solener.2014.02.011.

[22] D. L. Staebler and C. R. Wronski, "Reversible conductivity changes in discharge-produced amorphous Si," *Appl. Phys. Lett.*, vol. 31, no. 4, pp. 292–294, Aug. 1977, doi: 10.1063/1.89674.

[23] D. Wagner and P. Irsigler, "On the annealing behaviour of the Staebler-Wronski effect ina-Si:H," *Appl. Phys. A Solids Surfaces*, vol. 35, no. 1, pp. 9–12, Sep. 1984, doi: 10.1007/BF00620293.

[24] S. Silvestre, S. Kichou, L. Guglielminotti, G. Nofuentes, and M. Alonso-Abella, "Degradation analysis of thin film photovoltaic modules under outdoor long term exposure in Spanish continental climate conditions," *Sol. Energy*, vol. 139, pp. 599–607, Dec. 2016, doi: 10.1016/j.solener.2016.10.030.

[25] W. Kanchana and S. Sirisukprasert, "PV Power Forecasting with Holt-Winters Method," in *2020 8th International Electrical Engineering Congress (iEECON)*, Mar. 2020, pp. 1–4. doi: 10.1109/iEECON48109.2020.229517.

[26] E. Pieri, A. Kyprianou, A. Phinikarides, G. Makrides, and G. E. Georghiou, "Forecasting degradation rates of different photovoltaic systems using robust principal component analysis and ARIMA," *IET Renew. Power Gener.*, vol. 11, no. 10, pp. 1245–1252, Aug. 2017, doi: 10.1049/iet-rpg.2017.0090.

[27] J. Zhang, Z. Tan, and Y. Wei, "An adaptive hybrid model for day-ahead photovoltaic output power prediction," *J. Clean. Prod.*, vol. 244, p. 118858, Jan. 2020, doi: 10.1016/j.jclepro.2019.118858.

[28] M. Dhimish and A. Alrashidi, "Photovoltaic Degradation Rate Affected by Different Weather Conditions: A Case Study Based on PV Systems in the UK and Australia," *Electronics*, vol. 9, no. 4, p. 650, Apr. 2020, doi: 10.3390/electronics9040650.

[29] M. Theristis, A. Livera, C. B. Jones, G. Makrides, G. E. Georghiou, and J. S. Stein, "Nonlinear photovoltaic degradation rates: modeling and comparison against conventional methods," *IEEE J. Photovoltaics*, vol. 10, no. 4, pp. 1112–1118, Jul. 2020, doi: 10.1109/JPHOTOV.2020.2992432.

[30] T. Ishii, T. Takashima, and K. Otani, "Long-term performance degradation of various kinds of photovoltaic modules under moderate climatic conditions," *Prog. Photovoltaics Res. Appl.*, vol. 19, no. 2, pp. 170–179, Mar. 2011, doi: 10.1002/pip.1005.

[31] A. Cronin, S. Pulver, D. Cormode, D. Jordan, S. Kurtz, and R. Smith, "Measuring degradation rates of PV systems without irradiance data," *Prog. Photovoltaics Res. Appl.*, vol. 22, no. 8, pp. 851–862, Aug. 2014, doi: 10.1002/pip.2310.

[32] S. Silvestre, A. Tahri, F. Tahri, S. Benlebna, and A. Chouder, "Evaluation of the performance and degradation of crystalline silicon-based photovoltaic modules in the Saharan environment," *Energy*, vol. 152, pp. 57–63, Jun. 2018, doi: 10.1016/j.energy.2018.03.135.

[33] R. Singh, M. Sharma, R. Rawat, and C. Banerjee, "Field Analysis of three different silicon-based Technologies in Composite Climate Condition – Part II – Seasonal assessment and performance degradation rates using statistical tools," *Renew. Energy*, vol. 147, pp. 2102–2117, Mar. 2020, doi: 10.1016/j.renene.2019.10.015.

[34] M. C. Peel, B. L. Finlayson, and T. A. McMahon, “Updated world map of the Köppen-Geiger climate classification,” *Hydrol. Earth Syst. Sci.*, vol. 11, no. 5, pp. 1633–1644, Oct. 2007, doi: 10.5194/hess-11-1633-2007.
[35] A. Phinikarides, G. Makrides, B. Zinsser, M. Schubert, and G. E. Georghiou, “Analysis of photovoltaic system performance time series: Seasonality and performance loss,” *Renew. Energy*, vol. 77, pp. 51–63, May 2015, doi: 10.1016/j.renene.2014.11.091.

BIOGRAPHIES OF AUTHORS

Fatimazahra Oum’bark was born in Taroudant province-Morocco 1991. She received her engineering degree from the National High School of Mines of Rabat, in 2015 in Energy Engineering. She is currently pursuing her PhD degree with the department of metrology and information traitement at Ibn Zohr University, faculty of sciences in Agadir city. Her Research generally interests clean energy systems and artifictial intelligence. She can be contacted at fatimazahra.oumbark125@gmail.com.

Hicham Lotfi was born in 1981. He received his Ph.D. degree in Metrology and Information Processing, from Sciences Faculty-Ibn Zohr University, Agadir in 2013; his Master degree in the same institution in 2006. Since 2014, he has worked as a professor of Physics in Laâyoune Higher School of Technology Ibn Zohr University, Morocco. His research and teaching interests include Computer sciences, renewable energy, and building energy efficiency. He can be contacted at email: lotfi.hicham@yahoo.fr.

Amin Bennouna teaches Physics since 1980, won a Moroccan National Research Prize Distinction in 2009, led two energy companies (to 2005 and to 2018) and held several positions in the Moroccan Solar Industry Association from 1996 until 2016. He presently coordinates a network of 250 Moroccan energy researchers after having led an 'Innoproject' solar energy research carried by all the Moroccan Universities with IRESEN funds (2014-2018), and after having managed two multilateral European 'Medcampus' projects with EU funds (1990-1994). After having built an energy scenario (2007) for Morocco’2030 and signed more than 200 papers, he is presently updating his "Monograph of energy in Morocco" (first edition in 2011). He can be contacted at email: sindibad@uca.ac.ma.

El Houssaine Ouacha was born in 1987 in Tinghir, Morocco. He received his “License degree” in physics in 2010 at Faculty of Sciences; Agadir. Then he got there his “Master degree” in instrumentation in 2012. He completed his PhD in 2016 from the same institute. He is a professor at the Ecole Supérieure de l’Education et de la Formation of the Ibn Zohr University; Agadir.His primary research interests are focused on nondestructive evaluation of UHT milk by using ultrasonic technique. Recently, he engaged in studies of neural networks application in the field of renewable energies and nondestructive testing of composite materials. He can be contacted at email: ouacha0662@gmail.com.