Article citation info:
Sendjasni S, Yagoubi B, Daoud M, Belbachir N, Ziane A. Fault detection in photovoltaic systems using the inverse of the belonging individual Gaussian probability. Diagnostyka. 2023;24(1):2023112. https://doi.org/10.29354/diag/161318.

DIAGNOSTYKA, 2023, Vol. 24, No. 1

e-ISSN 2449-5220
DOI: 10.29354/diag/161318

FAULT DETECTION IN PHOTOVOLTAIC SYSTEMS USING THE INVERSE OF THE BELONGING INDIVIDUAL GAUSSIAN PROBABILITY

Salah SENDJASNI [1], Benabdellah YAGOUBI [1], Mohamed DAOUD [1], Nasreddine BELBACHIR [1], Abderrezzaq ZIANE [2]

[1] Department of electrical engineering, University of Mostaganem, Road Belahcel 27000- Mostaganem Algeria
[2] Unité de Recherche en Energie Renouvelables en Milieu Saharien, URERMS, Centre de Développement des Energies Renouvelables, CDER, 01000, Adrar, Algeria
[*] Corresponding author, e-mail: salah.sendjasni.etu@univ-mosta.dz

Abstract

This article addresses the problem of fault early detection in photovoltaic systems. In the production field, solar power plants consist of many photovoltaic arrays, which may suffer from many different types of malfunctions over time. Hence, fault early detection before it affects PV systems and leads to a full system failure is essential to monitor these systems. The fields of control and monitoring of systems have been extensively approached by many researchers using various fault detection methods. Despite all this research, to early detect and locate faults in a very large photovoltaic power plant, we must, in particular, think of an effective method that allows us to do so at the lowest costs and time. Thus, we propose a new robust technique based on the inverse of the belonging individual Gaussian probability (IBIGP) to early detect and locate faults in the power curve as well as in the Infrared image of the photovoltaic systems. While most fault detection methods are well incorporated in other domains, the IBIGP technique is still in its infancy in the photovoltaic field. We will show, however, in this work that the IBIGP technique is a very promising tool for fault early detection enhancement.

Keywords: Faults in photovoltaic systems, infrared image, Gaussian white noise, inverse probability

1. INTRODUCTION

Energy needs have become one of the biggest challenges for governments worldwide, where it continues to grow [1, 2]. Most energy production comes from fossil sources, and the consumption of these sources leads to an increase in gas emissions, which leads to an increase in global warming [3]. In addition, the excessive consumption of stocks of natural resources reduces it, which is dangerous for future generations. Therefore, considering other clean, renewable energy sources has become an urgent necessity [4].

Renewable energies are promising solutions [5] to compete with mass energies such as fossil and nuclear energies. Among renewable energies, photovoltaic energy is one of the most importantly free and cleans resources [6]. The PV market has witnessed remarkable growth in recent years [7]. However, like all other industrial systems, PV systems can be exposed to various malfunctions during their operation, and many different types of faults may occur during their operation over time and could lead to a loss in the produced energy and, thus, its low yield. In particular, Hot spots, Encapsulation faults, Cell cracking, Damaged interconnection, Breakdowns at the junction box, Bypass diode, Shade faults, short circuits, Ground faults, Open circuit faults, Line-line faults, MPPT and inverter faults, DC-DC Converter Faults and the Battery bank failures are worthy of mention because of their multiple effects on the above-mentioned systems. Any of these faults lead to a decrease in system performance, sometimes even total damage to the system, and thus a lack of energy [8, 9, 10]. Moreover, decreasing the profit of the installation, not to mention the maintenance cost to restore the system to normal condition.

In the literature, the fields of control and monitoring of photovoltaic systems have been addressed by many researchers using various methods, such as methods based on Electrical circuit simulation, Predictive models and comparison with real models, Statistical and Signal Processing-Based Techniques, Electrical signal approaches, Reflectometry Based Techniques, Artificial intelligence, power loss analyses, a method based on I-V characteristics, Imagery infra-rouge, [11, 12, 13, 14, 15]. In this work, we are particularly interested in early detecting and locating faults in photovoltaic systems in a solar power plant consisting of a large number of photovoltaic arrays. Early detection is crucial for avoiding further deterioration as well as photovoltaic system failure. We develop, therefore in this work, a very robust and efficient algorithm based on the inverse of the belonging individual Gaussian probability (IBIGP) technique applied to the power signal and infrared image of the photovoltaic system to early detect faults.

This work may be divided into three main sections: the first part describes in detail the IBIGP proposed algorithm, the second section deals with the application of this algorithm to the PV panel power curve to detect any abnormal system component behaviour, and the last, and may be the most important part, consists in the application of the IBIGP algorithm to the PV panel infra-red image to detect early micro-cracks.

2. MATERIALS AND METHODS

2.1. Experimental materials

The experimental measurements were carried out in Renewable Energy Research Unit in the Saharan Region (URER.MS), in Adrar, Southern Algeria.

Adrar is an excellent region for the installation of a photovoltaic station, thanks to their sunshine almost all year round and rare rainfall [16].

The photovoltaic plant station consists of 10 SM-250Wp silicon mono-crystalline solar modules installed at 28.88°S angle and an inverter Sunny Boy SB 2500. As shown in the following Fig. 1 [17].

(a) (b)

Fig. 1. ThePV system installation: (a) The 2.5 kW PV array, (b) inverter Sunny Boy SB 2500.

- Infrared thermal camera Flir T440 (320 x 240) (76 800 pixels) from 20 to 1200°C used for detecting the faults as a micro crack and all types of hot spot faults

2.2. IBIGP algorithm-based fault detection

Fault detection is primarily the first step before fault diagnosis. It mainly detects the changes that may indicate the presence of faults in the system. The detection technique, proposed in this work, follows a similar framework as the existing methods for fault detection: they characterize the normal behaviour of a system, and identify any significant changes from this normal and consider them as faults. More importantly is, however, the early detection of incipient faults which is extremely vital for the safety of the system as well as efficient implementation of a condition-based maintenance system. More accurate and robust algorithm for faults early detection in a photovoltaic system is, therefore, crucial for enhancing the safety and reliability of the system. We have, thus, suggested a very efficient algorithm based on the Inverse of the belonging Individual Gaussian Probability (IBIGP) for fault early detection. The strength of this technique is its ability to very early detect faults compared to the existing methods in the literature.

Fig. 2. The Infrared thermal camera Flir T440

First, we have to stress on the fact that the main idea of our IBIGP algorithm is to consider any fault (change) as a rare event compared to the normal behavior of the photovoltaic systems, and, hence, its probability given by equation (1) below, to belong to normal behavior should be very small. So, by inversing the probabilities of the abnormal behavior data, we obtain very big probability inverse values (2) corresponding to rare events (Faults). This IBIGP algorithm is described in the following;

First, we start by searching an adequate Gaussian white noise (GWN) [18] to fit the non-faulted (normal) signal (or image) behavior. However, since the whole signal (or image) is often not stationary, we segment it into small enough stationary intervals. Each of the latter will be, then, represented be an appropriate GWN. Once the optimal GWN for the normal signal/image is determined, we use its parameters (i.e.; variance and mean [19]) to compute the individual probability of each interval value of the abnormal (faulted) signal/image. Finally, we compute the inverse of these probabilities to obtain the IBIGP representation for fault early detection. In summary, this IBIGP algorithm steps are described as follows;

The Gaussian probability law is given by

$$\mathrm{P} = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(\mathrm{x}-\mathrm{m})^2}{2.\sigma^2}\right] \tag{1}$$

And its inverse is the following

$$\frac{1}{\mathrm{P}} = \sigma\sqrt{2\pi} \exp\left[\frac{(\mathrm{x}-\mathrm{m})^2}{2.\sigma^2}\right] \tag{2}$$

Where, σ^2 is the variance and m is the average.

1 - Segment the signal (or each matrix line of the image) into small enough stationary segments

2 - Compute the parameters (means and variances) of each of these normal segments using equations (3) and (4) below to represent each of them by a corresponding GWN model [20, 21].

$$\hat{\sigma}_i^2 = \frac{1}{L}\sum_{n=l-L}^{l-1}(\hat{W}_i(n) - \hat{m}_i)^2 \qquad (3)$$

$$\hat{m}_i = \frac{1}{L}\sum_{n=l-L}^{l-1}\hat{W}_i(n) \qquad (4)$$

Where $\hat{m}_i$ and $\hat{\sigma}_i^2$ are the estimated average and variance of each resulting power interval i.

$\hat{W}_i(l-L),\ldots,\hat{W}_i(l-1)$ Are the values of the i^{th} $(i=1,2\ldots I)$ power interval, L is the interval length and $l = i.L$.

3 - Use these two estimated parameters $\hat{m}_i$ and $\hat{\sigma}_i^2$ to reconstruct each normal GWN interval as follows;

$$\hat{W}_{ri} = \hat{\sigma}_i * \mathrm{rand}(1, L, 'n') + \hat{m}_i \qquad (5)$$

Where $rand(1, L, 'n')$ is a function built into Scilab software to generate Gaussian white noise of L samples.

4- Then aggregate these segments to reconstruct the entire power signal/image GWN model and then check the accuracy by comparing the reconstructed signal/image to the real signal/image by using the mean squared error (MSE). If the reconstruction is reasonable, save the GWN parameters, else, gradually reduce the segment length and return to step 2.

This process is repeated from step 2 to step 4 until an acceptable reconstruction corresponding to an MSE less than 0.01 is achieved.

5- Once an acceptable reconstruction is achieved, compute the inverse of the probability of each abnormal interval using the normal interval GWN parameters ($\hat{m}_i$ and $\hat{\sigma}_i$) in equation (2) to obtain the IBIGP representation.

3. RESULTS AND DUSCUSSION

3.1. Application of the (IBIGP) technique to faults early detection in the power signal curve

Figure (3) shows the average power signal provided by 10 panels for ten days. This curve represents the power without fault during July

The whole non-faulted power signal is shown in figure (3) and part of it, ranging from 300mn to 510mn corresponding to high power values, is shown in figure (4a). The faulted signal in the same range with two deliberate faults is illustrated in figure (4b). As it is observed by direct comparison, there is only one major change indicated by one peak down in figure (4b) whereas the second, corresponding to incipient fault, is smeared out or bathed in the signal. However, the results of the IBIGP algorithm illustrated in figure (5c) show clearly the presence of two major changes indicated by the two very pronounced peaks up in the IBIGP curve. Hence, the IBIGP technique makes the faults much more visible than the direct comparison of two curves.

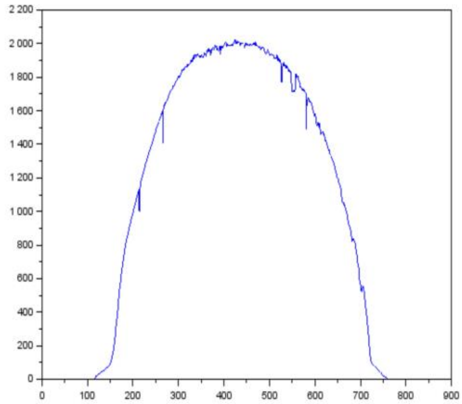

Fig. 3. Average power signal given by 20 panels.

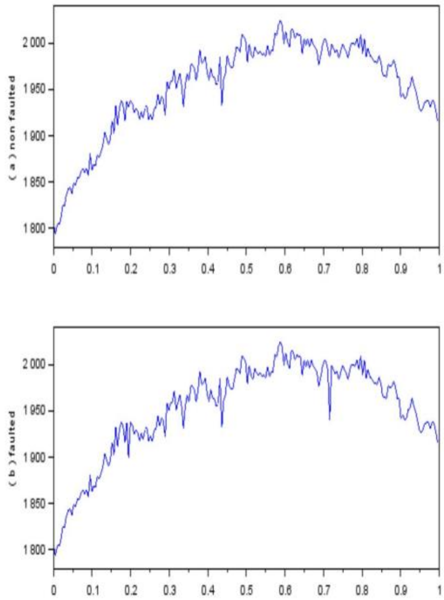

Fig. 4. a) Normal power signal (non-faulted), b) Faulted power signal.

3.2. Application of the (IBIGP) technique to faults early detection in the panel infra-red image

One of the most consequential damages to the panels is the micro-crack and the hot spot. These types of faults are usually caused either by shocks during their fabrication, transportation, or simply during their installation. If not detected early, it will lead more often to an enormous decrease in the PV module's performance over time. In general, faults may cause the cells to rise to undesired high temperatures, which can cause the panel glass to break due to stress caused by thermal expansion. Consequently, the panels may not be able to maintain their intended functionality. Faults, particularly in a large power plant, are often hard to locate but could be detected using an infrared image of the PV panel.

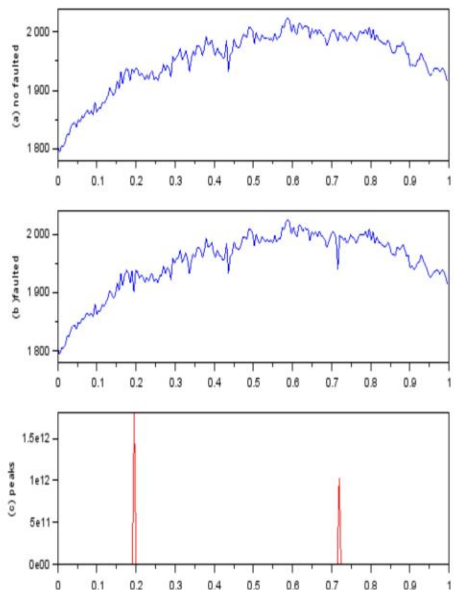

Fig. 5. a) non-faulted power signal and (b) faulted power signal, c) IBIGP of the faulted signal: Two separated and very pronounced peaks indicating the two faults

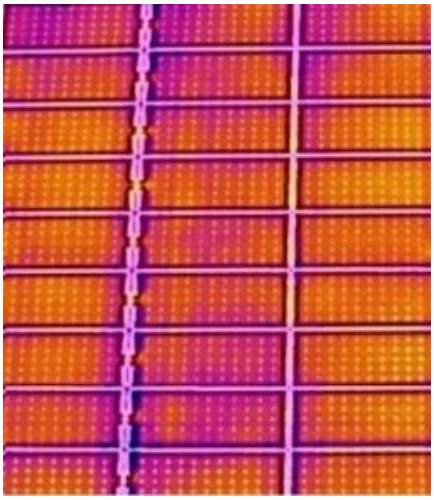

Fig. 6. Infrared image models without faults

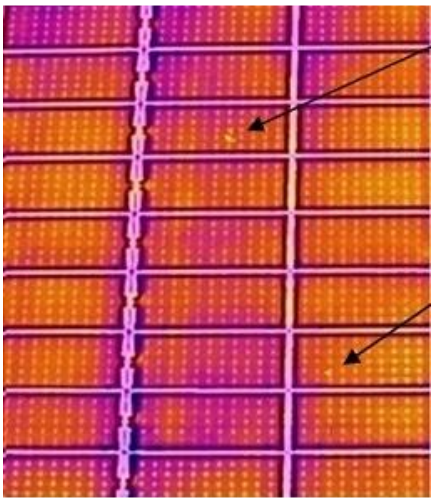

Fig. 7. Infrared image with two defects

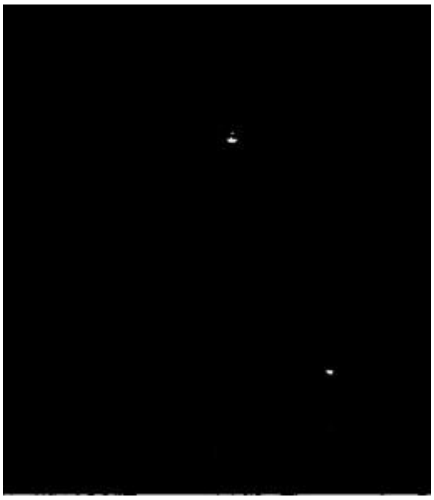

Fig. 8. IBIGP image: two bright spots representing two defects

The non-defected panel's infra-red image is illustrated in figure (6), and the defected panel infra-red image with two deliberate defects, is illustrated in figure (7). As it can be seen, these two defects are very hard to detect by just a simple comparison of the two infra-red images. Particularly in many photovoltaic arrays, it is a difficult task. In figure (8), after the Application of the (IBIGP) technique, the image shows clearly, however, the presence and the localisation of two bright spots. The latter represent the two defects that were incorporated deliberately in the photovoltaic panels to test the IBIGP detection quality.

4. CONCLUSION

This paper has proposed a technique based on the inverse of the individual Gaussian probability (IBIGP) to mitigate fault early detection and location in photovoltaic systems without too much computing complexity. We have shown that IBIGP applied to the power signal provided by the photovoltaic systems can detect very efficiently early irregularities such as pronounced peaks representing faults in the system. We have, furthermore, shown that the IBIGP is capable of detecting even those very tiny micro-cracks and the smallest hot spots in the PV panel infra-red image. In addition to the ability to detect faults, we have also shown that a major advantage of the IBIGP technique using a photovoltaic panel infrared image is that it allows greater memory storage than an image direct comparison. The IBIGP technique is, therefore, a very promising technique for faults early detection in photovoltaic systems; and can be considered as a very important step towards a better fault detection enhancement.

As a recommendation in this area is hybridization between this algorithm and another method for fault classification.

Author contributions: *research concept and design, S,S., D.D., Y.B., Z.A.; Collection and/or assembly of data, S.S., Z.A.; Data analysis and interpretation, S.S., D.D., Y.B.; Writing the article, S.S., Y.B., B.N., Z.A.; Critical revision of the article, B.N.; Final approval of the article, S.S., Y.B., B.N.*

Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

REFERENCES

1. Tansel C, Topcu M. Total, renewable and non-renewable energy consumption and economic growth : Revisiting the issue with an asymmetric point of view. Energy. 2018;152:64–74. https://doi.org/10.1016/j.energy.2018.03.128
2. Shahbaz M, Raghutla C, Chittedi KR, Jiao Z. The effect of renewable energy consumption on economic growth: Evidence from the renewable energy country attractive index. Energy. 2020;207:118162. https://doi.org/10.1016/j.energy.2020.118162
3. Science E. Substitution of energy needs with renewable energy sources. Earth and Environmental Science. 2021; 6th International Energy Conference. 012032. https://doi.org/10.1088/1755-1315/927/1/012032
4. Oberle B, Bringezu S, Hatfield-Dodds A, Zhu B. Global resources outlook 2019. natural resources for the future we want. 2019
5. Tabrizian S. Technological innovation to achieve sustainable development — Renewable energy technologies diffusion in developing countries.Sustainable Development. 2019;30:537-544. https://doi.org/10.1002/sd.1918
6. Kannan N, Vakeesan D. Solar energy for future world: - A review. Renewable and Sustainable Energy Reviews. 2016;62:1092–1105. https://doi.org/10.1016/j.rser.2016.05.022
7. Hayat MB, Ali D, Cathrine K, Lana M, Ahmed N. Solar energy — A look into power generation , challenges , and a solar - powered future. International Journal of Energy Research. 2019;43:1049-1067. https://doi.org/10.1002/er.4252
8. Aouchiche N. Défauts liés aux systèmes photovoltaïques autonomes et techniques de diagnostic - Etat de l'art. Journal of Renewable Energies. 2018; 21:247–265.
9. Pillai DS, Rajasekar N. A comprehensive review on protection challenges and fault diagnosis in PV systems. Renew. Sustain. Energy Rev. 2018;91:18–40. https://doi.org/10.1016/j.rser.2018.03.082
10. Omran AH, Ahmad N. A Survey of Different DC Faults in a Solar Power System. IEEE 8th Conference on Systems. Process and Control. 2020:11–12. https://doi.org/10.1109/ICSPC50992.2020.9305810
11. Triki-Lahiani A, Bennani-Ben Abdelghani A, Slama-Belkhodja I. Fault detection and monitoring systems for photovoltaic installations: A review. Renew. Sustain. Energy Rev. 2018;82:2680–2692. https://doi.org/10.1016/j.rser.2017.09.101
12. Appiah AY, Zhang X, Beklisi B, Ayawli K, Kyeremeh F. Review article review and performance evaluation of photovoltaic array fault detection and diagnosis techniques. 2019. https://doi.org/10.1155/2019/6953530
13. Ali K, Niazi K, Akhtar W, Khan HA, Yang Y, Athar S. Hotspot diagnosis for solar photovoltaic modules using a Naive Bayes classifier. Sol. Energy. 2019; 190:34–43. https://doi.org/10.1016/j.solener.2019.07.063
14. Colaprico M, De Ruvo MF, Leotta G, Vergura S, Marino F. DUBIO: a fully automatic Drones & cloUd Based Infrared monitoring system for large-scale PV plants. 2018 IEEE Int. Conf. Environ. Electr. Eng. IEEE Ind. Commer. Power Syst. Eur. (EEEIC/ I&CPS Eur. 2019. https://doi.org/10.1109/EEEIC.2018.8493736
15. Ziane A, et al. Detecting partial shading in grid-connected PV station using random forest classifier. Artificial Intelligence and Renewables Towards an Energy Transition. 2021;174:88–95. https://doi.org/10.1007/978-3-030-63846-7_10
16. Abderrezzaq Z, et al. Performance analysis of a grid connected photovoltaic station in the region of Adrar. 2017 5th International Conference on Electrical Engineering - Boumerdes (ICEE-B). 2017:1-6. https://doi.org/10.1109/ICEE-B.2017.8192229
17. Necaibia A, et al. Analytical assessment of the outdoor performance and efficiency of grid-tied photovoltaic system under hot dry climate in the south of Algeria. Energy Convers. Manag. 2018;171:778–786. https://doi.org/10.1016/j.enconman.2018.06.020
18. Yagoubi B. A geometric approach to a non-stationary process. In: Proceedings of the 2nd international conference on Mathematical Models for Engineering Science, and proceedings of the 2nd international conference on Development. 2011;2:179–183.
19. Hida Takeyuki, Masuyuki Hitsuda. Gaussian processes. American Mathematical Soc., 1993;120.
20. Rice SO. Mathematical analysis of random noise. The Bell System Technical Journal. 1944;23(3):282-332.
21. Chan SC, Zhou Y. On the performance analysis of a class of transform-domain NLMS algorithms with Gaussian inputs and mixture Gaussian additive noise environment. J. Signal Process. Syst. 2011;64:429–445. https://doi.org/10.1007/s11265-010-0494-5

Received 2022-11-06
Accepted 2023-02-16
Available online 2023-02-20

Sendjasni SALAH is a PhD student at the Department of Electrical Engineering at the faculty of science and technology of the University of Mostaganem, Algeria; He received the Master degree in Electrical Engineering from Chlef University, Algeria in 2017. He is a member of the laboratory "Renewable Energies and Electrical Systems" His research interests are the photovoltaic systems. E-mail: salah.sendjasni.etu@univ-mosta.dz

Benabdellah YAGOUBI received the M. Sc degree in Electrical Engineering in 1985 from Bel-Abbes University, Algeria and the Ph. D degree (amorphous thin films) (1986-1989) from Brunel University (UK). He was the head of the Signals and Systems Laboratory (1999-2003) and the head of the Department of Electrical Engineering (2005-2006). He is lecturing the theory of digital signal, systems modelling and identification, random processes and detection (1996-2016) at Mostaganem University, Algeria. He has been involved in some national projects, he is focusing on extracting useful information from mono-dimensional and multidimensional signals as well as on detection using the inverse of the belonging probability technique of a rare event to a Gaussian realization, as part of a national project. Further research interests are in real signals and models geometric representation based on Gram-Schmidt orthogonalization concept, as well as using a relative geometric space of observation.
E-mail: benabdellah.yagoubi@univ-mosta.dz

Mohamed DAOUD is a lecturer researcher at Abdelhamid Ibn Badis University of Mostaganem, Algeria. He received his Magister in Electronics, signal processing specialty from University of U.S.T. Oran, Algeria in 1997; he obtained his Ph.D. in Signal processing from Abdelhamid Ibn Badis University of Mostaganem, Algeria in 2014. His research interests are signal processing, image processing, solar energy, the electric vehicle, biomedical, automatism and several other topics related to signal processing. He was a member of several research projects. Email:mohamed.daoud@univ-mosta.dz

Nasreddine BELBACHIR received a B.Sc. degree in Electrical Engineering from the University of Relizane, Algeria, in 2013, and a M.Sc. degree in Electrical Engineering and Renewable Energy from the University of Mostaganem, Algeria, in 2015. Recently, received a Ph.D. degree in Electrical Engineering and Renewable Energy from the University of Mostaganem, Algeria. His research interests include the optimal integration of renewable energy in distribution grids, electric vehicles, power systems protection, PV parameters optimization.Heis a member of the laboratory "Renewable Energies and Electrical Systems".
Email: nasreddine.belbachir.etu@univ-mosta.dz

Abderrezzaq ZIANE received his Sc.D. degree in electronics engineering in 2018 from the University of Sidi Bel Abbes. He is a senior researcher at Renewable Energy Research Unit in Saharan Medium (URERMS), Center for Renewable Energy Development (CDER) Adrar, Algeria. Research topics: Photovoltaics, monitoring, machine learning, prediction and diagnostics. E-mail: a.ziane@urerms.dz