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Partial shading conditions for photovoltaic system using artificial neural networks technique

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ABSTRACT

Partial shading condition in solar photovoltaic (PV) systems is an inevitable problem due to the behavior of high nonlinear and unpredictable characteristics due to different shading states. However, several scientific works and research aimed to find approximate and expressive models of this nonlinear behavior using modern methods and techniques to allow researchers to find effective solutions to these critical situations. This paper aims to obtain the appropriate model for partial shading cases using artificial intelligence techniques through machine learning of neural network technology, based on experimental data of PV characteristics for different cases. This model allows for diagnosing the state of faults of Partial shading (PV) systems. Moreover, it allows the development of appropriate algorithms in order to maintain, perform, and prevent the complete shutdown of the systems. All results of the model photovoltaic partial shading characteristics for different situations based on the machine learning process confirm the effectiveness of the adopted technique after comparing it with the real data with a very acceptable margin of error.

Keywords: Partial shading, Modeling, artificial neural networks, photovoltaic system

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1. Introduction

Photovoltaic generation systems (PVG) technology has known a significant development due to several pros such as clean and low-cost maintenance available on the whole planet. Additionally, a study was done to reduce the greenhouse effect [1]. Solar photovoltaic (PV) energy is one of the most important renewable energies that directly produce electric energy from solar radiation [2].

To optimize the efficiency of PV systems, many works have been done to address problems that could lead to a decrease in the operation of these systems [3]. Among these problems is the phenomenon of shadows that affect the operation of the PV system. Partial shading passes through the sun partially and is caused by various things that can cover the surface of PV modules such as snow, sand, trees [4]. In this type of shading, the light reaching the cells is very small compared to other cells[5]. Several recent studies have been conducted to explain the effects of shading on the properties and operation of the PV system, and solutions have been proposed to address this problem [6] such as “Experimental investigation and modeling of photovoltaic soiling loss as a function of environmental variables”. They were suggested by the Institute of Research in Solar Energy and

New Energies - IRESEN, Green Energy Park, Morocco in 2020 [7]. Generally, the photovoltaic modules are associated in series to elevate the voltage and, in parallel, to increase the current to respond to the energetic needs of the load [8]. Practically, the photovoltaic array installation will not be exposed to the same level of irradiation which creates PSC [9]. When producing partial shading, the shaded cell becomes weaker and therefore will affect the performance of other cells [10]. Therefore, shading some cells can make the entire photovoltaic module unproductive. However, if photovoltaic panels are connected in series, the panel that produces the least determines the performance of the panel branch [11]. In recent years, research in this field has developed and varied to propose solutions to the effects of the phenomenon of shading [11], [12-15]. Normally, shading at a solar photovoltaic module happens partially along the module. The occurrence of shading could decrease the output power; thus, we try to minimize the effect of shading by the reconfiguration of modules. However, shading situations occur instantaneously and cannot represent the normal behavior of the module. Starting with the first practical application of solar modules on the NASA "Pioneer 1" space mission [16], other initial studies focused on the reliability and performance of modules subjected to reverse bias and, therefore, the degradation was localized in the hot spot [17,18]. Some methods contributions remained founded on artificial intelligence procedures, such as neural networks and fuzzy logic, in order to find solutions that contribute to the development of the arena of photovoltaic energy and its implementation as a source for electricity production [19]. In this work, artificial neural networks have been proposed to model the effect of partial shading on the functioning of the photovoltaic system. Studies on ANN started at the beginning of the 20th period and were established so rapidly that they reached this level [20]. It has remained effectively used in recent centuries in several fields such as energy, electronics, and robotics [21]. In previous work, the partial shading of the PV system was considered the most common fundamental problem and it is important to address it and improve the performance of the system. Hence, the most important step for studying and researching solutions to the problem is to obtain the simulated model for the various cases of partial shading under different conditions. Accordingly, many analytical and data models for specific conditions have been made. However, research on a global model that simulates the different conditions and cases remains to address these fundamental problems in the photovoltaic system [2], [6],[10], [13], [20,21].

An automotive and telecommunications ANN is an algorithm that learns, chooses and accepts consequences such as our mind procedures. These methods can also obtain the result by using the data obtained in case of insufficient data. The neural network is a computational model whose design is inspired by real human neurons and is one of the most common artificial intelligence techniques that allow decision-making based on precipitations rather than formal logical thinking [22,23]. A simple artificial neuron is a computational element with one or more numerical inputs and outputs. From an architectural point of view, artificial neural networks can be classified into two types: multilayer perception (MLP) and radial basis function networks (RBF) [24].

In this work, we used a network of MLP neurons consisting of three layers. Input layer with two neurons: "voltage when entering the PV panel (practical measurements) and immediate error", a hidden layer with a variable number of neurons between (2 and 16) and the output layer: "the current provided by the neural model of the PV panel." For the hidden layer, we used the experimental data through which we tested several values of neurons in order to choose the number that gives the error in smaller modeling. The obtained results show that the proposed neuronal network model reflects the actual behavior of the PV panel under different conditions partial shading with a very low modeling error.

2. Characteristics of the photovoltaic system under partial shading conditions (PSC)

We expose the use of artificial neural networks (ANN) to model the behavior of a monocrystalline silicon PV module SUN-80Wcphotovoltaicpanel when it is exposed to the phenomenon of partial shading. This model will allow further study of this phenomenon and its impact on the characteristics of photovoltaic systems for different metrological conditions and, thus, make predictions to avoid injuring the PV panel and accelerate its ageing. The modeling method suggested here is not envisioned for an exact photovoltaic system model and can be practical to diverse categories and models though the obtained model for a system will not be valid for other systems, the technique used will remain identical. Photovoltaic cells are optoelectronic mechanisms that directly convert sunlight into electricity through a process called a photovoltaic effect. They are made using semiconductor materials having intermediate properties between conductors and insulators.

2.1. Modeling of photovoltaic solar cell

As illustrated in Figure one and by smearing the KCL, the output current (I_{pv}) of a photovoltaic module is defined as:

$$I_{pv}=I_{ph}-I_0[exp(q(V_{pv}+I_{pv}.\ R_s)/A.n.K.T)-1]-(V_{pv}+I_{pv}.R_s)/R_p) \tag{1}$$

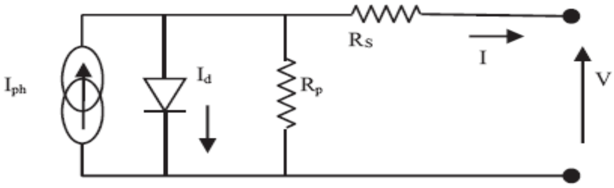


Figure 1. Solar cell diode model

Where, A: is the ideal factor of the junction; Iph: is photo-current created by the cell; I_0: is diode current which represents the internal leak to a cell due to the p - n junction of the cell; V_{ph} : the voltage across the cell; R_p: is hunt resistors represent leaks around the p-n junction due to impurities and on the cell corners; R_s: is serial resistance that symbolizes the mass resistance of the semiconductor material, the Ohmic, and contact resistors at the cell connections; q: is the charge of the electron (1, 6.10-19 C), and K: is Boltzmann constant (1, 38.10-23J/K).

3. Results and discussion

We conducted the study in constant conditions: sunlight: 800 (watts/m2) and temperature: 30 degrees (C°). Then, we selected a SUNTEC unit of its 80Wc (4x9 = 36) cells to study the properties of I-V and P-V without and under the presence of partial shading. In this experiment, the shading patterns are classified into four patterns: no shade (0% shaded), 9 of 36 PV panels (25% shaded), 18 of 36 PV panels (50 % shaded), 27 of 36 PV panels (75 % shaded), and 36 of 36 PV panels (100 % shaded). The module used in this work is illustrated in Figure 2.

Figure 2. Suntec-80wc module

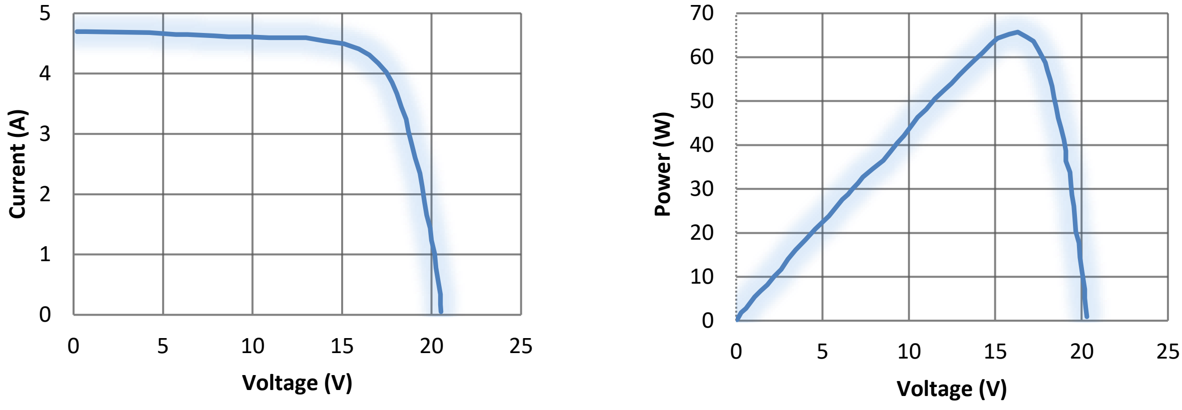
The modeling error of the neural model of the current-voltage characteristic is the cumulative square error between the current (I_d) required (practical measurements) and the output current of the neural model, it is calculated as follows:

$$E_{qc} = \sum^{N} (I_d\,(i) - I_{nn}\,(i))^2 \tag{2}$$

Where: N: is the number of training data, I_d (i): is the desired value of the current measured in practice, I_{nn} (i): is the current value when outputting the neural model.

3.1. The characteristics without shading

Figure 3 illustrates the real properties of I-V and P-V in the photovoltaic module specified in the strength condition without any shading on the cells. We have noticed that the maximum current delivered by the photovoltaic module is equal to I_m = 4.9 (A) and that the maximum power is equal to Pm = 69(W).



(a) (b)

Figure 3. Real data characteristics of I-V and P-V for PV solar without shading

3.2. The characteristics with shading

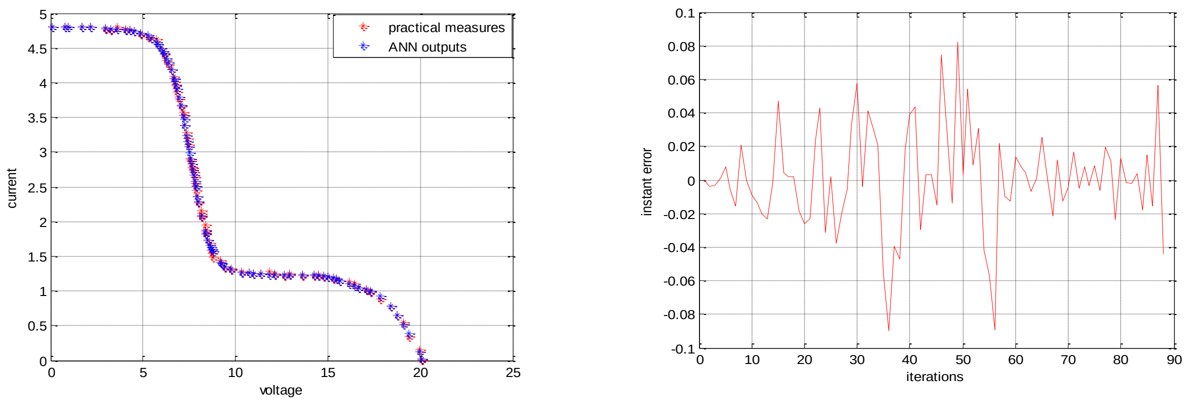
Table 1 shows the modeling errors acquired for diverse numbers of neurons in the hidden layer. It is observed that the model with eight neurons gives the lowest cumulative quadratic error.

Table 1. Number of neurons and corresponding error.

Number of neurons	Cumulative quadratic error	Number of neurons	Cumulative quadratic error
2	17.7429	7	2.6312
3	14.8961	8	0.4658
4	12.2985	10	1.7660
5	7.5101	12	1.0361
6	5.8920	16	2.9449

- Case (A):25 % shading condition

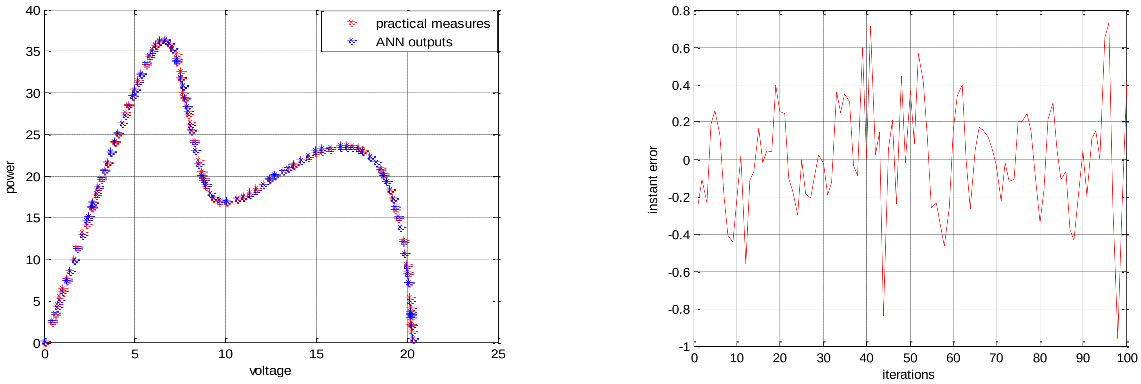
Figure 4 correspondingly represents the fourth characteristic, the consistent instant error, the PV property, the corresponding immediate error in the 25% shaded (9 of 36 PV panels), and the corresponding instant modelling error.



(a) (b)

Figure 4. Properties of I-V for PV solar and the error of the model with 25% shaded

In Figure 5, we remarked that the cumulative quadratic modelling error is equal to 0.0018 for the current voltage with an average squared error of 2.0922e-03. In shade at 25%, the cumulative quadratic modelling error is equal to 0.4658 for the power-voltage characteristic with an average of 0.0047.

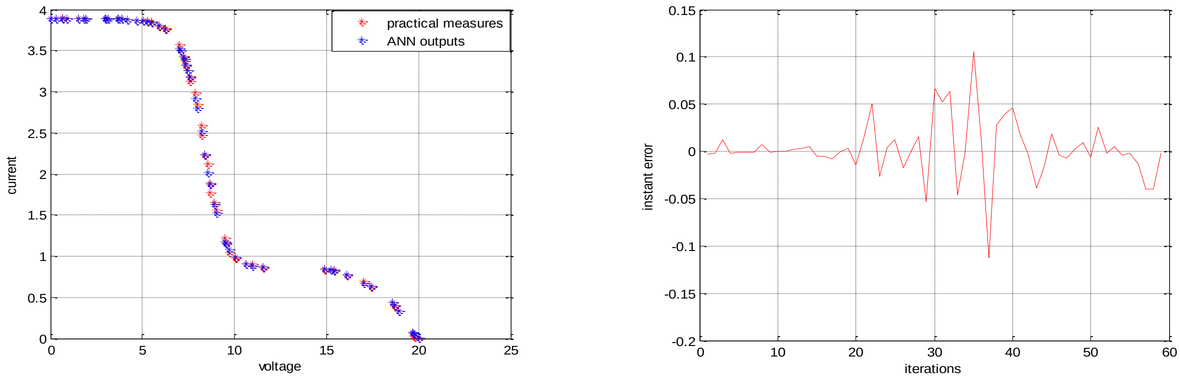


(a) (b)

Figure 5. Properties of P-V for PV solar and the error of the model with 25% shaded

- Case (B): 50 % shading condition

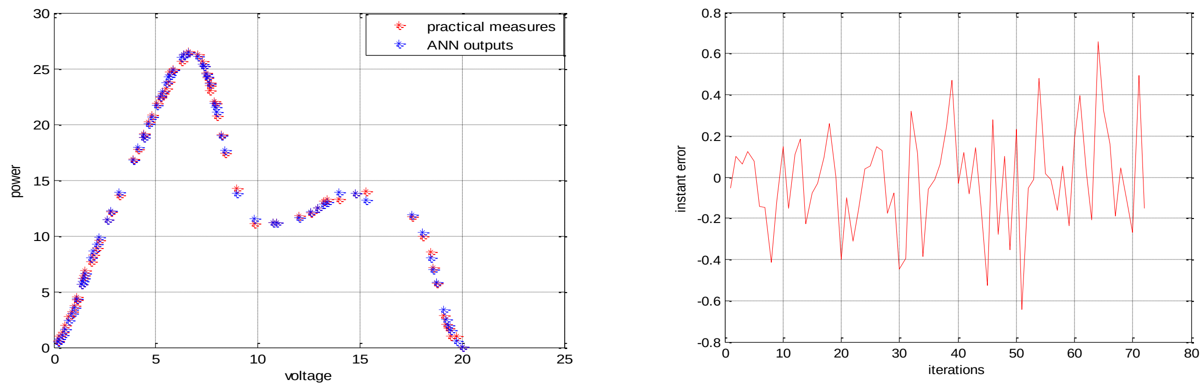
For the same 8-neuron neural model, the practical measurements for the 50% shading (18 of 36 PV panels) case are used. Figures 6 (a; b) represent the I-V and P-V characteristics of the photovoltaic module shaded at 50% and the corresponding instant modelling error.



(a) (b)

Figure 6. Properties of I-V for PV solar and the error of the model with 50% shaded

In Figures 7 (a; b), the cumulative quadratic modelling error is equal to 0.0194 for the current-voltage property with an average quadratic error of 3.2536e-04. We noticed that the cumulative quadratic modelling error is equal to 0.7996 for the power-voltage characteristic with an average of 0.0111.

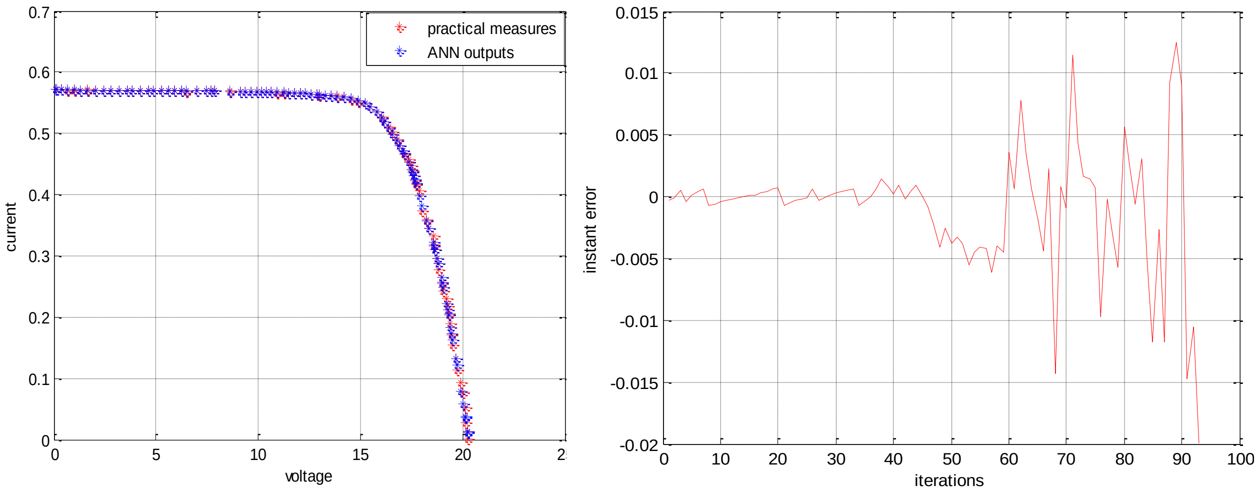


(a) (b)

Figure 7. Properties of P-V for PV solar and the error of the model with 50% shaded

- Case (C):75 % shading condition

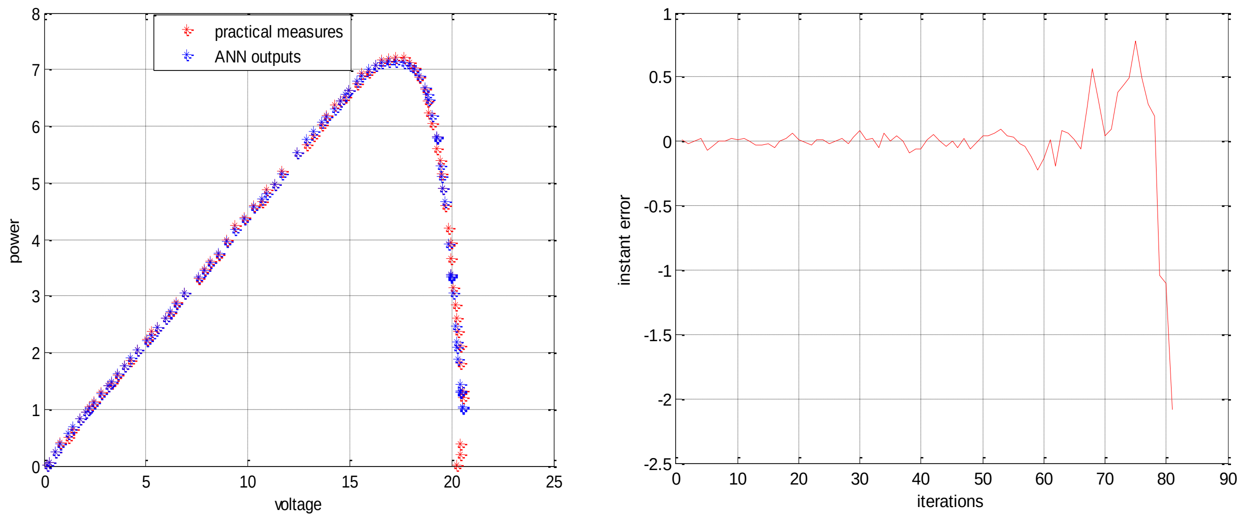
Figure 8 indicates the I-V and P-V characteristics of the photovoltaic module shaded at 75% (27 of 36 PV panels) and the corresponding instant modelling error. Conclusions (11 pt, Sentence case)



(a) (b)

Figure 8. Properties of I-V for PV solar and the error of the model with 75% shaded

In Figures 9 (a, b), in the case of a 75%shading, the cumulative quadratic modelling error is identical to 0.0071for the current stuff of the voltage with an average squared error of 7.6540e-05. For the power-voltage characteristic, the cumulative quadrature modelling error is equal to 0.0847 with an average of 0.0010.

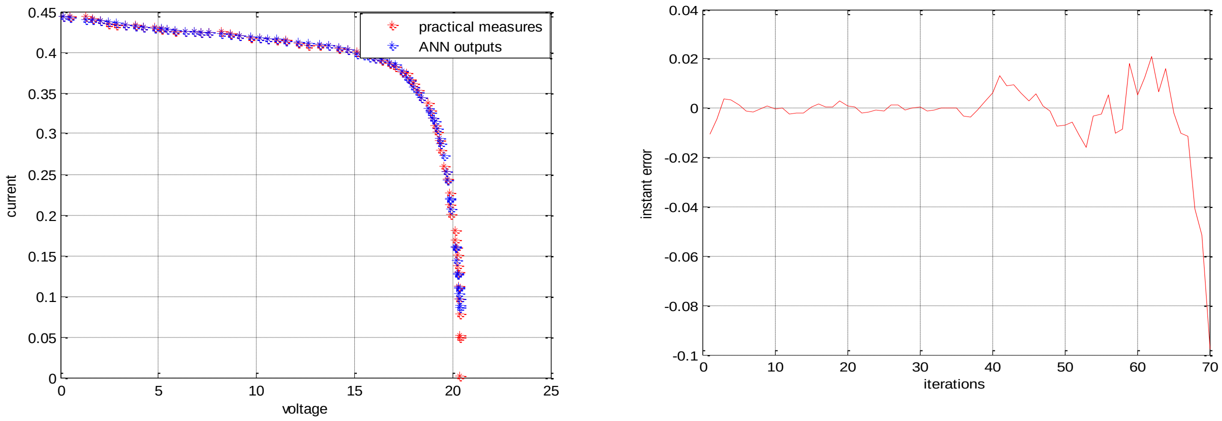


(a) (b)

Figure 9. Properties of P-V the for PV solar and the error of the model with 75% shaded

- Case (d):100 % shading condition

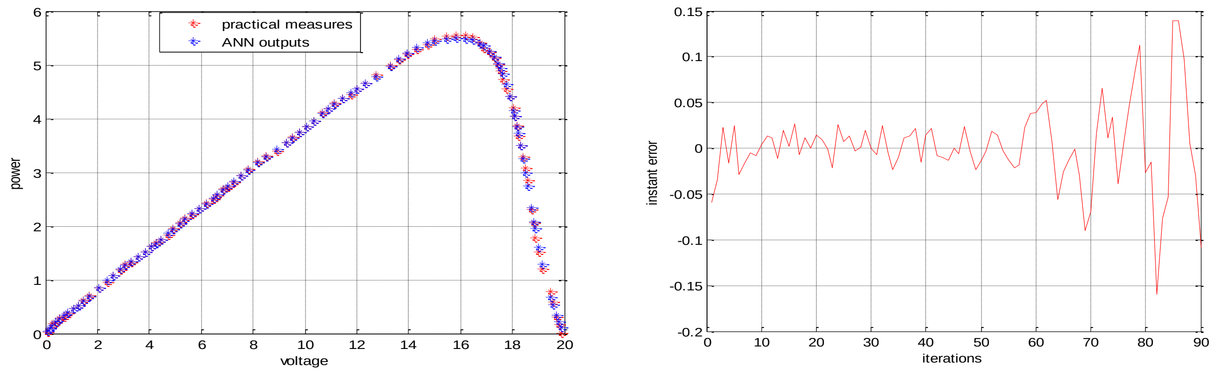
Figures 10 (a; b) represent the I-V and P-V characteristics of the photovoltaic module shaded at 100% (36 of 36 photovoltaic panels) and the corresponding instant modelling error.



(a) (b)

Figure 10. Properties of I-V for PV solar and the error of the model with 100% shaded

In Figures 11 (a; b), in100 % shading, the cumulative quadratic modelling error is equal to 0.0268 for the current voltage with an average squared error of 3.8232e-04. In this case, the cumulative quadratic error is equal to 0.0229 for the power-voltage characteristic with an average of 2.5485e-04.



(a) (b)

Figure 11. Properties of P-V the for PV solar and the error of the model with 100% shaded

3.3. Cases comparison

Table 2 illustrates the results achieved after the experimental and then modelling the photovoltaic panel by means of the intelligent neural network method.

Table 2. Comparison of panel characteristics in different partial shading conditions.

shading	Maximum Power (W)	Current (A)	maximum squared error (P-V)
Case (A)	37.2	4.60	0.9179
Case (b)	26.1	3.71	0.4371
Case (c)	7.23	0.58	4.3374
Case (d)	5.60	0.45	0.0255

After the results obtained, we consider that the neural model obtained has already inverted the effect of partial shading on the electrical properties of shaded diodes.

It has been said that the short-circuit current (I_{cc}) of the photovoltaic module is directly influenced by the increased shading rate. This effect is justified by the restriction of the panel area exposed to radiation which directly influences the generated photo-current. Furthermore, the open-circuit voltage (V_{co}) of the considered solar panel and the maximum power (P_{max}) decrease with the increase of the shading rate.

The power loss is dissipated as heat through the shaded part of the panel. The shape factor is also influenced with the increased shading rate as shown in the previous figures. Moreover, the form factor (FF) influences the increase in the shading rate. This increase is mainly due to the decrease of both the term (V_m. I_m) and the efficiency of photovoltaic conversion (η) decreases rapidly with the increase in the number of cloaked cells. This is confirmed by the behaviour of both P_{amx} and FF parameters. These results are acceptable, and the resulting model will enable us to infer the effects of partial shading on the overall behaviour of photovoltaic systems.

4. Conclusions

In this work, the modeling of PV systems without shading was introduced, and then experimental data on the effect of partial shading on PV was carried out in order to study its effect on the characteristics and performance of PV cells. Hence, artificial neural networks have been used due to the behaviour of this highly nonlinear system, and this tool has been suggested for its effectiveness and power for complex data processing. Therefore, many samples for disparate cases were taken at 25%; 50%; 75%, and 100% partial shading for machine learning and neural model validation.

The used experimental data showed that the resulting I-V and P-V curves were strongly influenced by partial shading conditions. The behaviour of the photoelectric system decomposes under partial shading and distortion of electrical properties (current and voltage). Consequently, the deformation of the characteristics of I-V and P-V reveals a decrease in short-circuits current and maximum power. As a result, the increase in partial shading in this system leads to a decrease in current and energy at the reflexion point and thus affects its efficiency. The results of the model confirm the effectiveness and the importance of using this tool to obtain the asymptotic model, and after comparing the results obtained with the real data gave an acceptable error concerning the photovoltaic power.

The resulting neural model will allow further studies on the effect and the incidence of shading on the characteristics of PV systems for different metrological conditions; thus, making predictions to avoid damaging the PV panel and accelerating ageing.

Declaration of competing interest

The authors declared that they have no conflicts of interest in this work.
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.

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