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Monitoring, diagnosis and localization of the partial shading fault in a photovoltaic power plant with an approach by artificial neural networks

***Abstract**. This paper aims to propose a useful modeling diagnostic method for solar plants. The study was performed on the basis of the localization of the failing panel obtained by an effective comparison of measured output voltages and estimator voltages. The comparison is done with the ideal solar plant using learning approach based on artificial neuronal network (ANN). The partial shading failure was detected by the given equation $d^2\Delta V/dI^2>0$. The obtained results using MATLAB/Simulink environment show a satisfactory performance in terms of rapidity and precision under variable shading conditions.*

***Streszczenie.** Celem artykułu jest zaproponowanie użytecznej metody diagnostycznej modelowania dla elektrowni słonecznych. Badania przeprowadzono na podstawie lokalizacji uszkodzonego panelu uzyskanej poprzez efektywne porównanie zmierzonych napięć wyjściowych i napięć estymatorów. Porównanie jest dokonywane z idealną elektrownią słoneczną przy użyciu podejścia uczenia opartego na sztucznej sieci neuronowej (ANN). Częściowe zacienienie zostało wykryte za pomocą podanego równania $d^2\Delta V/dI^2>0$. Uzyskane wyniki w środowisku MATLAB/Simulink wykazują zadowalające działanie pod względem szybkości i precyzji w zmiennych warunkach zacienienia. (**Monitoring, diagnostyka i lokalizacja zwarcia częściowego zacienienia w elektrowni fotowoltaicznej z podejściem sztucznych sieci neuronowych**)*

Keywords: Solar Plant, Partial Shading Failure, Diagnostic system, Modeling of the Photovoltaic (PV) Plant System, Artificial Neuronal Network (ANN).
Słowa kluczowe: awaria częściowego zacienienia, system diagnostyczny, modelowanie systemu elektrowni fotowoltaicznej (PV), sztuczna sieć neuronowa (ANN).

Introduction

To meet the world's needs of electrical power production, a new means of energy called PV system was introduced. This system converts solar radiations to electricity using the photovoltaic effect. However, the system showed its imperfection because of shading phenomenon caused by veiling the sun rays from the PV modules.

In order to solve shading problems, several researchers have introduced different methods of diagnosis in order to represent solar cells behaviour.

Recent works on photovoltaic system diagnostic done by Arrar.H et al. The study has proposed a modeling of a photovoltaic solar system based on the effect of partial shading. They suggest a correct procedure modeling of PV system under partial shading failure. The latter was validated by comparing I-V and P-V characteristics of STP PV model with the measured data under partial shading condition [2]

For the purpose of classifying all possible fails that could accrue in PV system, Arrar and co-workers have proposed methods such as FDD for multiple methods of mal function detection and diagnosis.

For different methods of mal function detection and diagnosis, they proposed methods such as FDD method to classify all possible fails that could accrue in PV system.

Moreover, two predominant mathematical models (two-diode cell) were presented by [3, 4]. Even though the first one proved its accuracy, but it has contained a large number of electrical parameters in addition to a long period if treatment. Due to its simplicity, the second model built with only five parameters is widely used by researchers because of its simplicity that's based on five parameters only. Later, Ishaque [5] reduced the number of parameters from five to four, with a view to enhance the output performance of the model. His work was based on the Newton-Raphson method.

A simple diagnostic method for PV modules was proposed by [6], the research has determined the number of open short circuit of PV modules in a PV plant considering economic factors. Therefore, their results were compared to experiment measurements. These results were found to be in good agreement with experimental measurements.

[7], selected parameters of the photovoltaic module and the results of the laboratory tests of the powers caused by the partial shading defect in a small area of 0.89% of the surface of the PV panel, which caused a significant loss greater than 11% of maximum power, but his work has lacked concrete solutions for partial shading fault monitoring.

This paper is structured as follows: first section includes a realization of an equivalent circuit of a solar cell. Then, a model of PV module is created with MATLAB/Simulink software leading to the final modeling of the solar plant. In the second section, an Artificial Neuronal Network ANN is used for the learning of the estimator in an ideal solar planet. The third section represents the strategy of the applied diagnostic which is based on localization and detection of partial shading failure. We aim to provide a simple diagnostic method of the shading effect on PV plant.

Modeling and simulation

A PV panel is the heart of a solar plant system. The scheme equivalent shown in Fig. 1 has been carried out using the Powersim under MATLAB/Simulink.

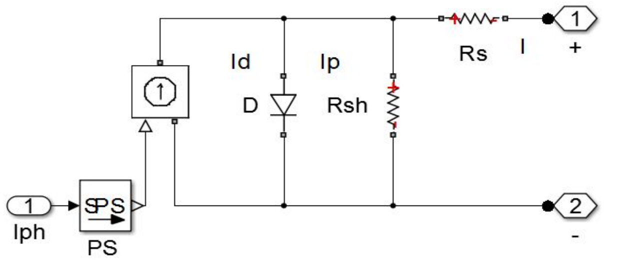


Fig.1. Electrical equivalent circuit of a PV cell realized by MATLAB/ Simulink software.

The current provided by the PV generator is expressed by analytic equations [8]

$$I = I_{sc} - I_d - I_p \tag{1}$$

where: I – current supplied by the cell density, I_{SC} – short-circuit cell current, I_d – diode current, I_P – current though resistor.

$$I_p = \frac{V + R_s I}{R_p} \tag{2}$$

where: I_P– photon current, V– voltage across the cell, R_S – series resistance of PV cell, R_p– hunt resistor
where:

$$I_d = I_0\left[\exp\left(\frac{qV_d}{KT}\right) - 1\right] \tag{3}$$

where: I_0 – saturation current, q – electron charge, V_d – diode voltage, K – Boltzmann constant, T – effective cell temperature.
where:

$$V_d = \frac{V + R_s I}{a} \tag{4}$$

where: a – ideality factor of the diode.
The characteristics of a PV cell's intensity-voltage are:

$$I = I_{sc} - I_0\left[\exp\left(\frac{q\left(V + IR_s\right)}{aKT}\right) - 1\right] - \frac{\left(V + IR_s\right)}{R_p} \tag{5}$$

The photocurrent I_{SC} is given by:

$$I_{sc} = \frac{R_p + R_s}{R_p} I_{pv} \tag{6}$$

where: I_{PV} – current generated by the PV cell distance.
When the condition I_{sc}= I_{pv} is guaranteed, we get in return an optimized operation of the program accompanying the PV simulation, we obtain [9]:

$$I = I_{pv} - I_0\left[\exp\left(\frac{V + IR_s}{V_t a}\right) - 1\right] - \frac{\left(V + IR_s\right)}{R_p} \tag{7}$$

where: V_t – thermal junction voltage.
The PV generated current I_{pv} is influenced by the solar radiation and temperature according to the following equation [8, 9]:

$$I_{sc} = \frac{R_p + R_s}{R_p} I_{pv} \tag{8}$$; $$I_{pv} = \left(I_{pv,n} - K_i \Delta T\right)\frac{G}{G_n} \tag{9}$$

where: K_i – current/temperature coefficient, T – effective cell temperature, G – solar radiation, G_n – solar radiation reference.
with:

$$\Delta T = T - T_n \tag{10}$$

where: T_n – reference temperature.
According to equations (3) and (4), the diode current can be evaluated by:

$$I_d = I_0\left[\exp\left(\frac{\left(V + IR_s\right)}{V_t a}\right) - 1\right] \tag{11}$$

where:

$$I_0 = \frac{I_{sc,n} + K_i \Delta T}{\exp\left(\frac{V_{oc,n} + K_i \Delta T}{V_t a}\right) - 1} \tag{12}$$

Modeling of the PV plant system

The design of a solar PV system contains 15 panels polycrystalline; this system is composed of 3 subsystems connected in series, each subsystem contains 5 panels with the same connection, more details can be seen in Fig. 2.

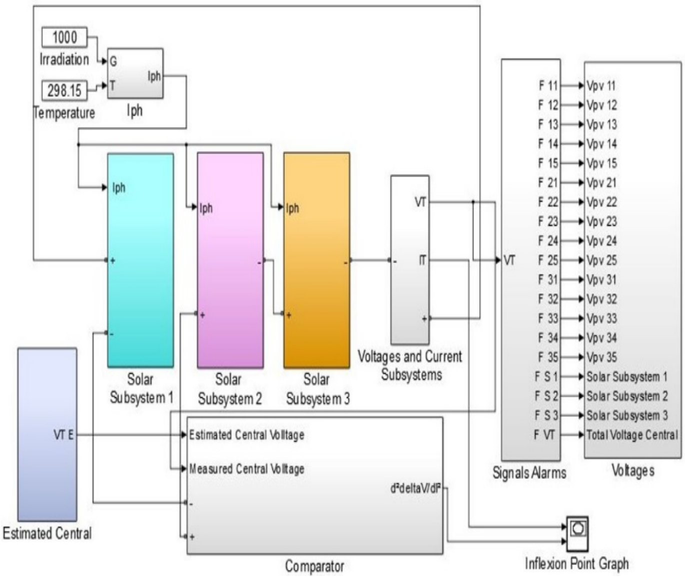


Fig.2. The block component of the PV central realized by MATLAB/Simulink software

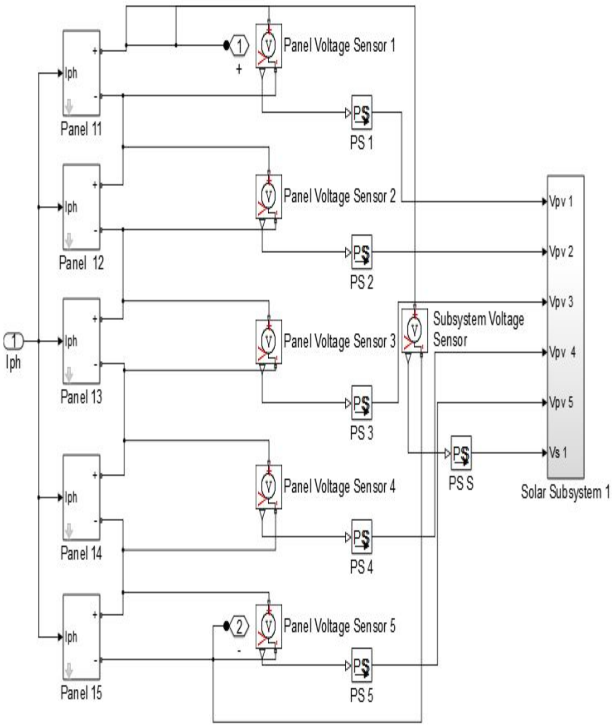


Fig.3. The block component of the PV subsystem realized by MATLAB/Simulink software

Learning of PV plant by Artificial neural network

As any energy production system, photovoltaic (PV) installations has to be monitored to enhance system performances and early diagnostic of failures, for more reliability. There are several photovoltaic monitoring strategies based on the output of the plant and its nature. Monitoring can be performed locally on site or remotely. It measures production and focuses also on verification and follow-up of converter and communication devices for an effective operation. Up to now, new methods of failures diagnostic of PV system has been developed.

However, given the evolution of PV installations, more advanced monitoring techniques are continuously under investigation. In this paper, major photovoltaic system failures are addressed and some techniques for photovoltaic monitoring were proposed in recent studies.

In order to study the partial shading failure, it's we must compare the voltages derived by the PV plant with solar estimator's voltages, obtained by intelligent approach (ANN) [10, 11, 12] that requires learning from a database corresponding to its inputs and outputs. The main objective of the ANN model is to detect possible failures in the examined PV system shown in Fig. 2. The ANN model has been developed as following [13]:

- Selection of input and output variables.
- Data set normalization.
- Selection of network structure.

The estimator output voltage are given in Fig. 4 together with the ANN output voltage. Agreement voltage between estimator and ANN model is acceptable ,it's important to mention that negligible error where considered in the simulation.

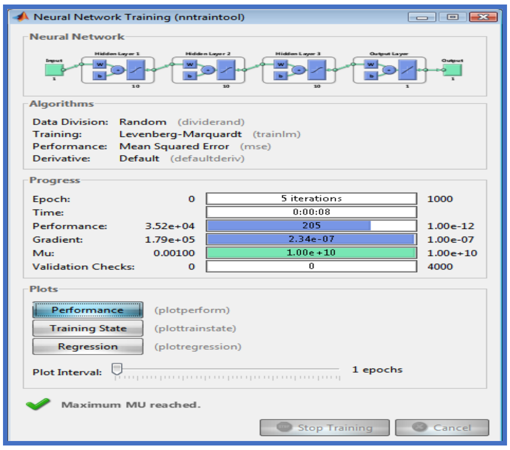


Fig.4. Learning neural network of the solar planet

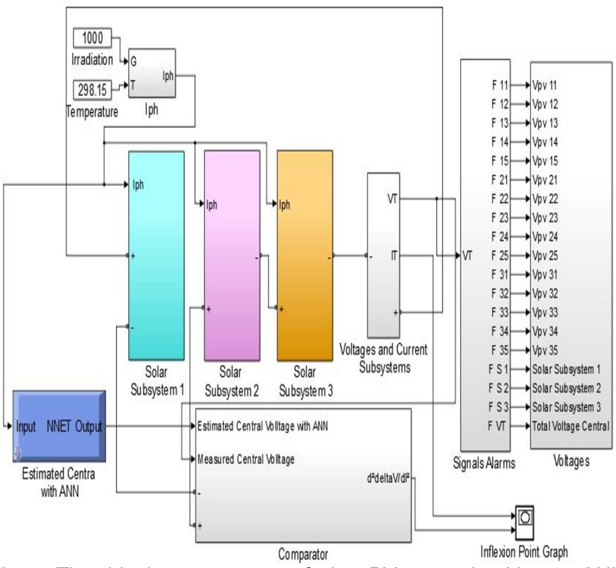


Fig.5. The block component of the PV central with an ANN estimator realized by MATLAB/Simulink software

Localization and Detection of partial shading failure

In this section the development of localization system needs 19 voltage sensors , 15 sensors related to each panel, 3 related to each subsystem, and a long sensor related to the PV plant output as showed in Fig. 3.

Fig. 4 shows the detection of partial shading failure.

The failure is detected only if ($d^2 \Delta V/dI^2$) > 0, the sensor in the system is on, if ($d^2 \Delta V/dI^2$) < 0,if shading is not detected the sensor is off [12]. The procedure used to explain localization and detection of shading failure is shown in Fig. 5.

The first inputs are ; temperature (T°) , insolation (G),panel tension(V_{PV}), and the incertitude of measurement instrument.

The solar plant voltage is determined by:

(13) $$V_T = \sum_{i=1}^{N} V_{Si}$$

where: V_T – the solar planet voltage, V_S – the subsystem voltage, N – the number of series cells per module.

If there are no failing panels (F= 0), the subsystem voltage is evaluated by:

(14) $$V_S = nV_{PV}$$

where: V_{PV} – the panel voltage, n – number of panels in the subsystem.

when the failure is detected(F= 1), the subsystem voltage is described by:

(15) $$V_S = (n-f)V_{PV} + \sum_{j=1}^{f} V_{PVf}$$

where: f – the number of failed panels, V_{PVf} – faulty panel voltage, F – the signal representing the absence or the presence of the failure.

Then, to spot the failing panel, its tension should be compared to a threshold of a normal tension panel (E) calculated by:

(16) $$E = V_{PVE} \pm \varepsilon$$

where: JV_{PVE} – estimated panel voltage y, ε – uncertainty about the system and the measurement instrumentation.

If the measured tension of the panel (V_{PV}) is less than the normal panel's voltage, the indicator alarm is on (F=1) which show the failing panel, that confirm the existence of a flex point; if not, there is no failing panel (F= 0).

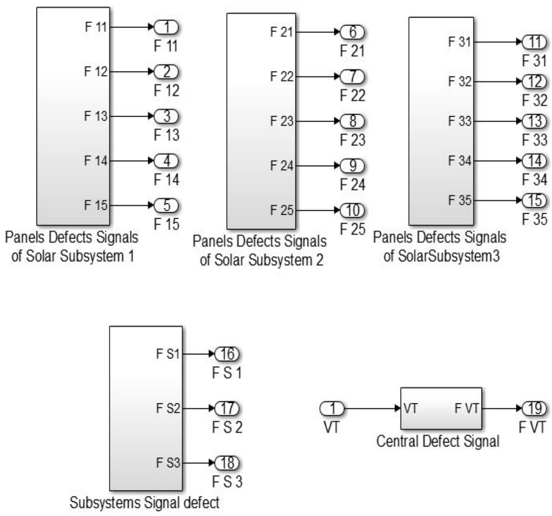


Fig.6. Block diagram of assembled alarm signals

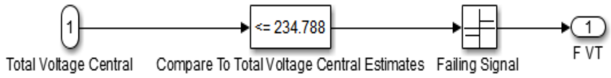


Fig.7. Comparator of the total voltage of the PV plant with the estimated threshold

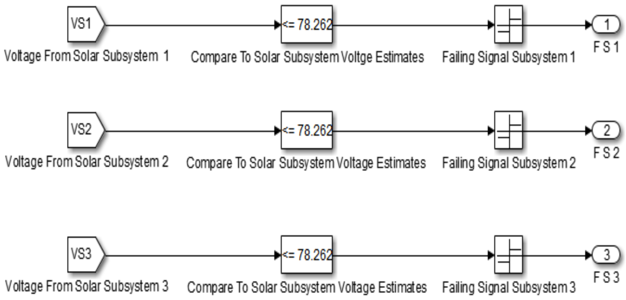


Fig.8. Comparator of the output voltages of the 3 solar groups with the estimated thresholds

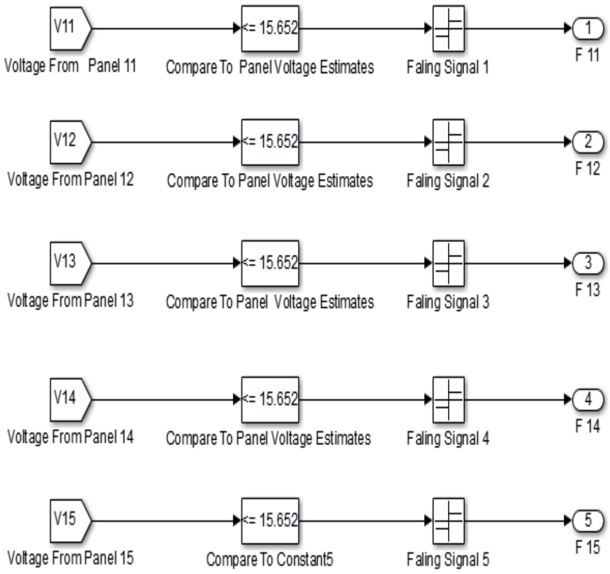


Fig.9. Comparator of the output voltages of the PV panels (example of group 1) with the estimated thresholds.

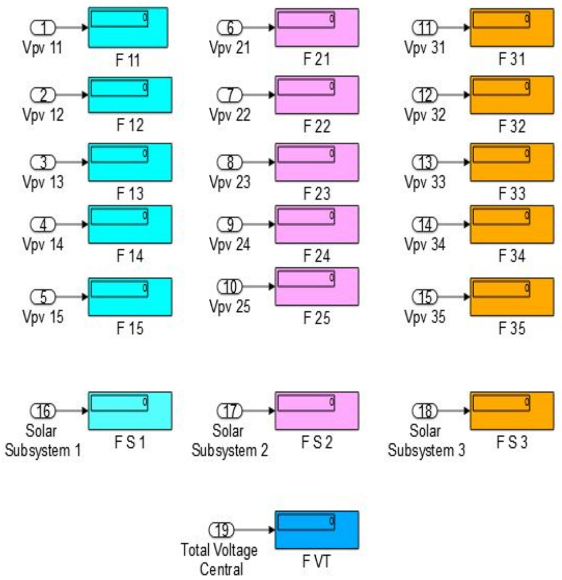


Fig .10. The block component of the signal's alarms of the PV central

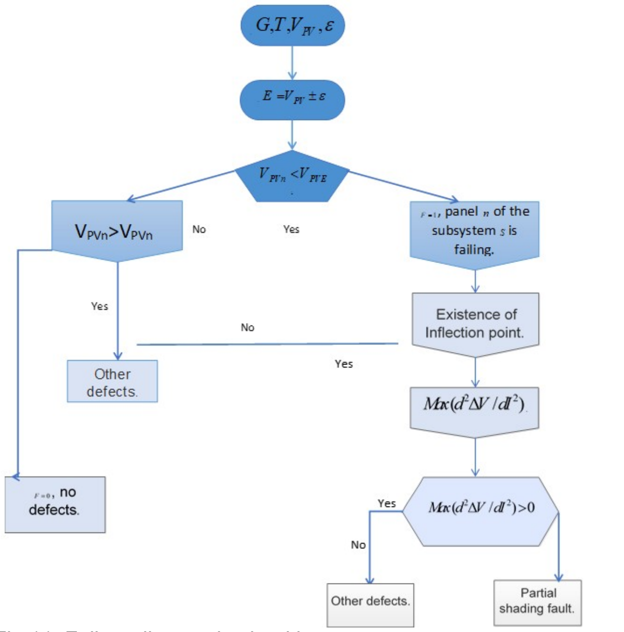


Fig.11. Failure diagnostic algorithm.

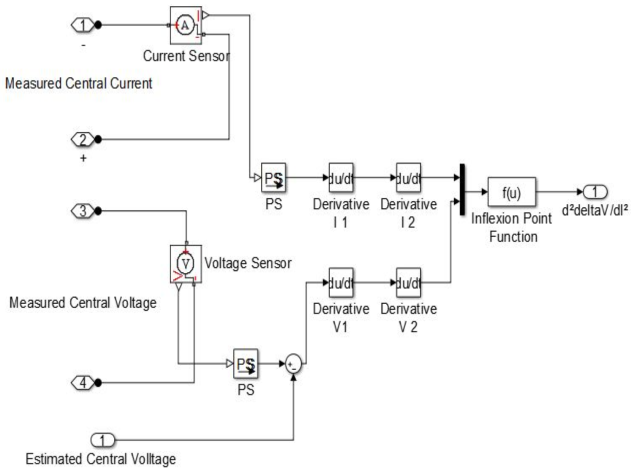


Fig.12. Block components of the failure detection system realized by MATLAB/Simulink software

Results and discussion

To diagnose and localize partial shading defect, we applied three percentages of partial shading on three panels from the photovoltaic plant.

Every partial shading percentage was applied on each panel respectively: 25%, 50% and 75%, the localization of this defect is shown in Fig. 13.

The MSX_60 used panels characteristics are mentioned in the table below [14].

Table 1. The MSX_60 panel characteristics

I_{sc} [A]	V_{oc} [V]	I_{mp} [A]	V_{mp} [V]	N_s cels	KV [V/°C]
3.80	21.10	3.50	17.10	36	-0.1055
KI [A/°C]	R_s [Ω]	R_{sh} [Ω]	I_{ph}[A]	I_s [A]	A
0.0025	0.2160	203.68	3.8045	3.582e-8	1.2354

The obtained results were found using MATLAB/Simulink software, under these climatic conditions: Temperature: 298.15 K and Radiation: 1000 W/m². Fig. 13 illustrates the effect of partial shading degradation. It can be observed that when the percentage of shading increase, the output photovoltaic parameters decrease.

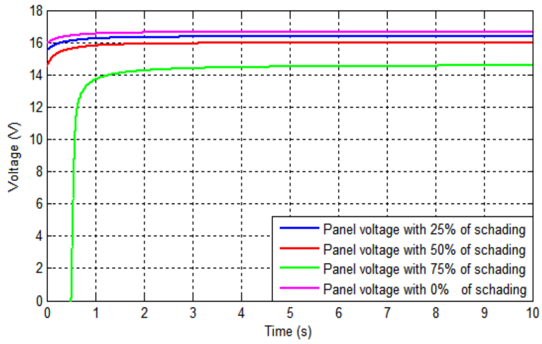
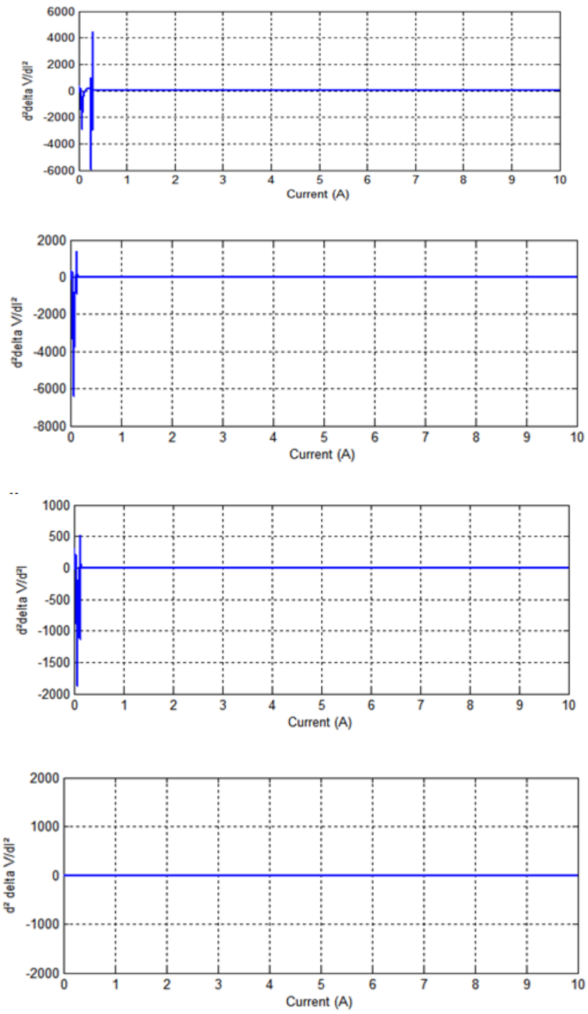


Fig.13. The effect of partial shading degradation

a)



d)

Fig. 14. The inflexion points of the partial shading degrade a 75% of the partial shading, b 50% of the partial shading, c 25% of the partial shading, d 0% of the partial shading.

In addition, Table 2 summarizes all obtained results.

Table 2. The deferent values of the partial shading degradation.

Partial shading percentage	Max of (d²ΔV/dI²)
0 %	0
25 %	521,6
50 %	1379,8
75 %	4433,05

Conclusions

This work was oriented toward the diagnosis of partial shading defect on a photovoltaic plant. The proposed approach is based mainly on the analysis of the characteristic I(V). for that, it should be noted that the shading phenomena affect the characteristic I(V).

This method combines the use of tension sensors and mathematical method of function point test as well as the error analysis of the solar system starting from the presence of the inflect point.

In the aim of validating the present method, simulation results using artificial neural network approach prove the efficiency of the proposed method and its perfect compliance with referenced theorical studies. The suggested diagnosis method that is based on the effect's detection and localisation model was carried out with MATLAB/Simulink software.

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