ISSN : 2335 - 1357

Mediterranean Journal of Modeling and Simulation

MJMS 03 (2015) 001-009

Artificial neural Network-Based modeling and monitoring of photovoltaic generator

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ARTICLE INFO

Article history :
Received September 2014
Accepted January 2015

Keywords :
PV panel monitoring ;
Artificial neural network ;
PV panel diagnosis.

ABSTRACT

In this paper, an artificial neural network based-model (ANNBM) is introduced for partial shading detection losses in photovoltaic (PV) panel. A Multilayer Perceptron (MLP) is used to estimate the electrical outputs (current and voltage) of the photovoltaic module using the external meteorological data : solar irradiation G (W/m2) and the module temperature T (ř C). Firstly, a database of the BP150SX photovoltaic module operating without any defect has been used to train the considered MLP. Subsequently, in the first case of this study, the developed model is used to estimate the output current and voltage of the PV module considering the partial shading effect. Results confirm the good ability of the ANNBM to detect the partial shading effect in the photovoltaic module with logical accuracy. The proposed strategy could also be used for the online monitoring and supervision of PV modules.

1. Introduction

Monitoring systems play a very important role in the field of photovoltaic solar energy, due to the number of failures and losses that can happen during the operation of a given PV installation (panel/array) such as : bad contact between the photovoltaic modules, panels or cells [1-4], partial shading on the PV panel/array [2, 5-10], corrosion, as well as PV cells aging [6]. An application monitoring system alerts the operator when the PV generator performance thresholds are crossed. Various monitoring solutions have been proposed to enhance the PV systems performances, and to reduce the time, the cost of faults diagnosis and maintenance operations [11].

In [1] authors have proposed a method based on the inspection of the series resistance of photovoltaic panel/array using the measurement of the I-V characteristics of the PV panel/array, which is compared with the series resistance given by the manufacturer in the data sheet, the aim of this method is the detection of loose connections between

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the PV modules and/or cells. This method is based on a complex measurement for the determination of the series resistance ; it is not accurate in the case of large PV installations due to the very small value of the series resistance of the PV panel/array.

Another method based on the estimation of the PV module's temperature has been proposed in [1]. The aim of this method is to detect any abnormal increasing in the temperature of the PV module/array. This method requires a complex mathematical relationship, which needs a large calculation time, and it is not accurate in the hot regions, where it cannot easily distinguish between the normal and the abnormal increasing of the temperature.

In [5], the authors proposed an expert system for the PV systems monitoring and diagnosis, this method investigates the database of the site where PV systems are installed ; it detects the loss in the energy generated by the PV systems, caused by failures in the DC-DC and DC-AC converters. It is based on the comparison of the actual output of any PV system component, and the stored database in their normal operating state. This method is always related to the database of the site where PV system is installed, which must be updated every month, and it requires the use of a computer and cannot be used in a real time. So, the expert system cannot distinguish between a normal and abnormal power decreasing in the case of natural shading (for example : passage of clouds,. . .).

Numerous other methods exploit a satellite data and services for the monitoring and failure detection in the PV systems [11,12]. In [13], the authors implemented a wireless remote monitoring and control system of a solar photovoltaic distributed generator for micro grid applications. [14] presents a prediction approach in monitoring of PV power systems, This proposed approach is based on the calculation of the residual difference between the model predicted and the actual measured power parameters .

In this paper, a novel approach based on the neural network is introduced to detect faults in a PV module, especially in the case of partial shading problem. The developed monitoring system enables the early fault detection to be identified. The designed approach could be used for a single PV panel as well as for a large PV installation. In addition, it is also easy to be implemented in a field programmable gate array (FPGA) platform [15,16] for the following tasks :

Real time monitoring of PV systems : in this case, the model will be installed at the same site of the PV system, and through a Radio Frequency link, the estimated output power can be transmitted to the control room. In this way the system can generate alarm for operators when it detects an important error between the produced energy of the PV system (measured energy), and the estimated energy.

Maintenance of PV systems : in which case the model achieved can be implemented on a special electronic instrument for the maintenance of PV systems. It can be used by operators when intervention for maintenance of PV systems.

In this study, we applied this new intelligent approach to monitor the partial shading on the BP150SX solar panel. Monitoring results are presented and given versus the number of shaded cells in the PV panel.

2. Presentation of the proposed monitoring approach

In this section, the new monitoring approach is presented ; the block diagram of the developed system is shown in Figure 1. As can be seen, the developed monitoring system enables early system faults to be detected via the calculation and the analysis of the residual error in the power generation between the predicted PV performances (ANNBM predictor) and the measured PV performances. The ANNBM must be located at the same conditions with the PV module.

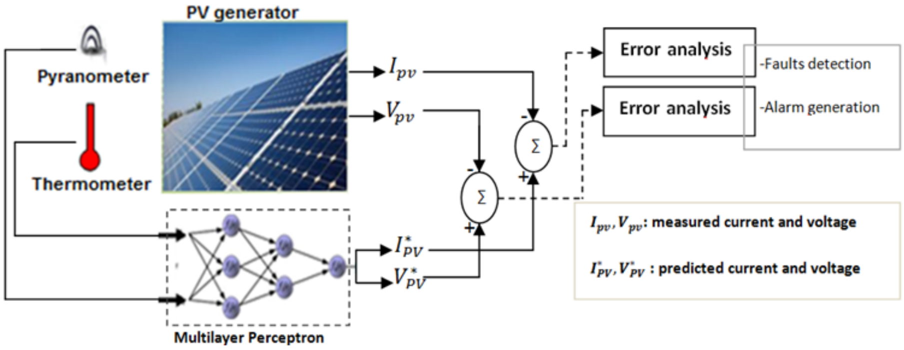

Fig. 1. PV generator monitoring using artificial neural network.

2.1. Network architecture

The proposed method is based on the utilization of an MLP. As shown in the Figure 2 , the network architecture is a three layers, it consist of an input layer, one hidden layer, and one output layer. In this application, the MLP is used as a PV panel modulator [16], it predicts the performances of the photovoltaic module/panel (IPV and VPV). For this, external meteorological data are used as inputs : solar irradiation $G(W/m^2)$, and temperature $T(°C)$.

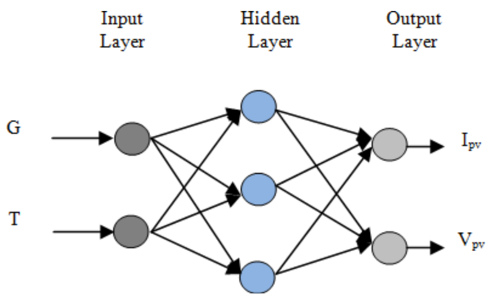

Fig. 2. Multilayer perceptron neural network.

2.2. Network training and validation

The MLP network was trained using a large experimental database of the BP150SX PV module under normal operating state and variables externals conditions. As shown in Figure 3 ; the used database has two inputs namely : G and T, and two targets represented by I_{pv} and V_{pv}.

The MLP was trained using MATLAB's Resilient back propagation training algorithm (RPROP), input and target vectors were linearly scaled between -1 and +1 to simplify training process . The best structure of the MLP that gave best performances is presented in Table 1. The training performance is achieved after 10000 iterations using the mean square error (MSE) as training criteria. The network has been evaluated using a separate database collected during a period of 10 days with 60 data per day (data was recorded during the operation of the PV generator every 15 minutes). In Figure 4, we show the validation results using data collected during one day of operation. From Figure 4, it is clear that the trained MLP can easily follow the targets and generalize well, it predict correctly the output performances of the PV panel (current and voltage) under variables external meteorological data (G and T). So, we can conclude that the proposed MLP is well designed and trained.

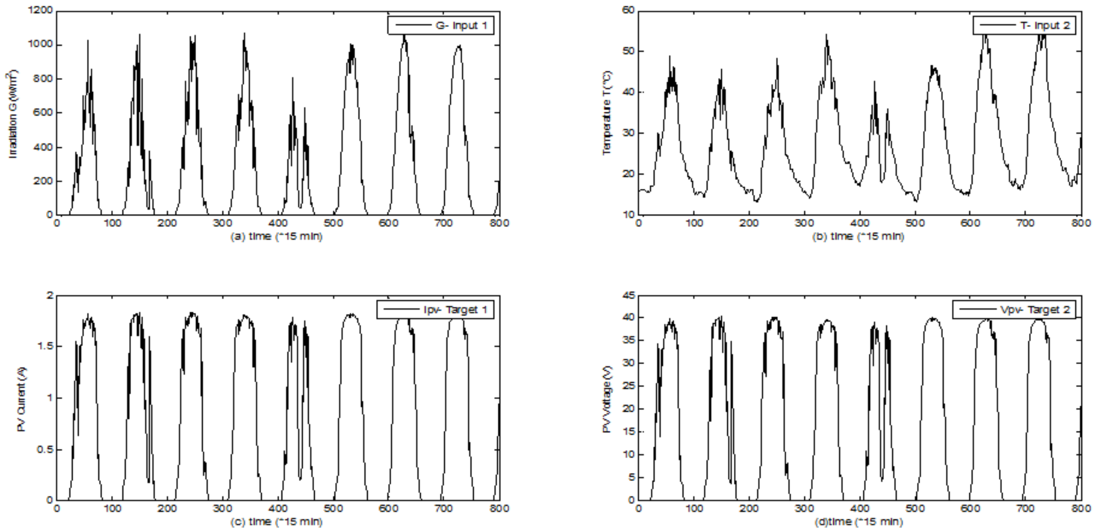

Fig. 3. Training data base.

Table 1. Selected architecture of the neural network.

Number of the hidden layers	02
Number of neurons	22 , [10-10- 2]
Training algorithm	RPROP
Performance (MSE) at 10000 Iterations	0.00139

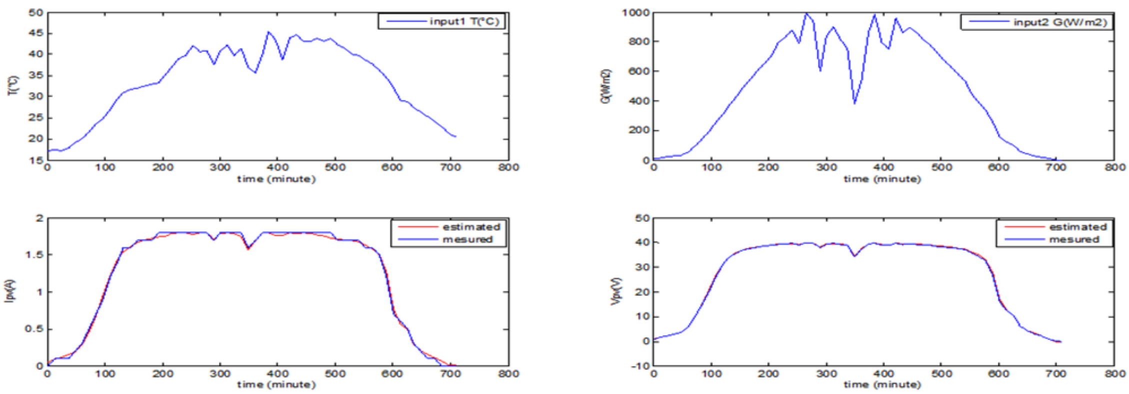

Fig. 4. Training and validation results.

2.3. Partial shading monitoring

In this study, the MLP designed is used to predict and estimate the PV output power in the presence of partial shading of the PV panel (BP150SX). The main goal of this proposed system is to warn the operator if any losses caused by partial shading occur, various tests are considered under a fix resistive load ($R = 20\Omega$), and variable number of shaded cells (the number of shaded cells is varied between 05 and 50, see Figure 5). The direct irradiation G of a shaded cell is considered as $0W/m^2$.

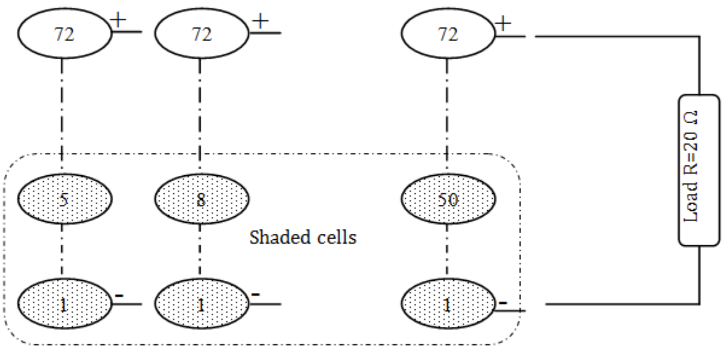

Fig. 5. Application of the partial shading on the BP150SX PV panel.

In the first step of the proposed monitoring approach, the ANNBM estimate the electrical output performances of the PV panel under variable conditions. In the second step, the system of monitoring evaluates the error between the measured output named y_i , and the estimated output named Y_i^*.

Two errors are considered for the evaluation, the first is the simple error (absolute value of the simple error), as given in the Equation (1).

$$E_i = |y_i - \mathrm{y}_i^*| \tag{1}$$

Where, E is the error between the measured and the estimated PV panel output.

y_i is the measured output of the PV panel, Y_i^* is the estimated output of PV panel.

The second is the accumulated error (error accumulated during 1 day for example), the mean of squared errors MSE is considered in our study, and is given by the mathematical relationship (2) as follow :

$$MSE\,(n) = \frac{\sum_{i=1}^{i=n} (y_i - y_i^*)^2}{n} \tag{2}$$

Where, n is the number of data samples.

The proposed system warns the operator when the error (E_i) or (MSE) exceeds a certain value of threshold (the threshold is fixed by the operator).

In the case of the output current monitoring, the MSE is computed as follows :

$$MSE_{Ipv}\,(n) = \frac{\sum_{i=1}^{i=n} \left(I_{pv.i} - I^*_{pv.i}\right)^2}{n} \tag{3}$$

where I_{pv} is the measured current of the PV panel. I_{pv}^{*} is the estimated output current of the PV panel.
n is the number of data ($n = 60$ for the case of our study).
In the case of voltage monitoring, the MSE is computed as follows :

$$MSE_{V_{pv}}(n) = \frac{\sum_{i=1}^{i=n}\left(V_{pv.i} - V_{pv}^{*}.i\right)^{2}}{n} \tag{4}$$

where V_{pv} is the measured output voltage of the PV panel. V_{pv}^{*} is the estimated output voltage of the PV panel.
This new strategy of monitoring is applied on the BP150SX PV panel, the main characteristics of this panel are cited in the Table 2.

Table 2. Electrical characteristics of the BP150SX

Maximum power (Pmax)	150W
Voltage at Pmax (Vmp)	34.5V
Current at Pmax (Imp)	4.35A
Short-circuit current (Isc)	4.75A
Open-circuit voltage (Voc)	43.5V
Number of series cells Ns	72

3. Results analysis and discussion

In this section, we present the results of the proposed approach of monitoring using the experimental data.
Table 3 present the results of the shading monitoring using the proposed new approach, during 02 days;

3.1. First day results :

In the case of PV current monitoring, the value of the MSE value is 0.0071 A2 if only 05 cells are shaded and increases to 1.04 A2 when 50 cells are shaded.
In the case of the PV voltage monitoring, the MSE vary between 4.55V2 when only 05 cells are shaded (Figure 6-b) and 501.74V2 when 50 cells are under shade (Figures 7-b).

3.2. Second day results :

In the case of PV current monitoring, the MSE has the value of 0.0066 A2 when 05 cells only are shaded, and increases to 0.9419 A2 when 50 cells are shaded in the case of current output.
In the case of the voltage monitoring, the MSE vary between 3.43 V2 when only 05 cells are shaded and 458.74V2 when 50 cells were shaded.
From the presented results, we can confirm that the value of the MSE increases when the number of the shaded PV cells increase.

Table 3. PV panel monitoring results.

Number of shaded cells	1st Day MSE(I_{pv}) (A2)	MSE(V_{pv}) (V2)	2nd day MSE(I_{pv}) (A2)	MSE(V_{pv}) (V2)
05	0.0071	4.5538	0.0066	3.4375
08	0.0224	11.6810	0.0177	9.4067
10	0.0368	18.3047	0.0292	15.0639
15	0.0862	41.6926	0.0701	35.5704
18	0.1258	60.5937	0.1054	52.1684
25	0.2337	118.7836	0.2118	104.3087
30	0.3570	173.0143	0.3161	153.2597
40	0.6309	314.3900	0.5710	283.3562
50	1.0433	501.7445	0.9419	458.0874

Figures 6, and 7 shows the same results, we can clearly see the remarkable variation of the error (MSE) between the two presented cases;

Figures (6-a and 6-b) shows respectively the variations of the error MSE between the measured and the estimated current (I_{pv}) and voltage (V_{pv}) during 1 day, the case of 05 shaded cells is token.

Figures (7-a and 7-b) shows respectively the variations of the error MSE between the measured and the estimated current (I_{pv}) and voltage (V_{pv}) during 1 day, the case of 50 shaded cells is presented.

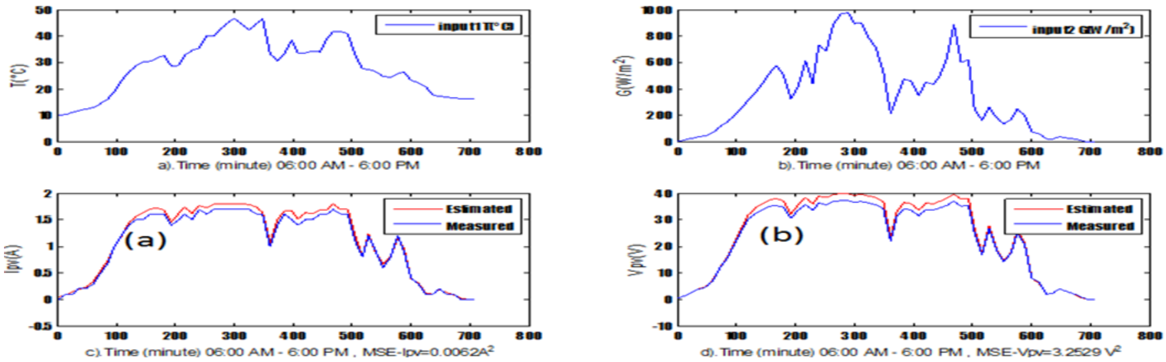

Fig. 6. PV panel performances with 05 PV cells under shading.

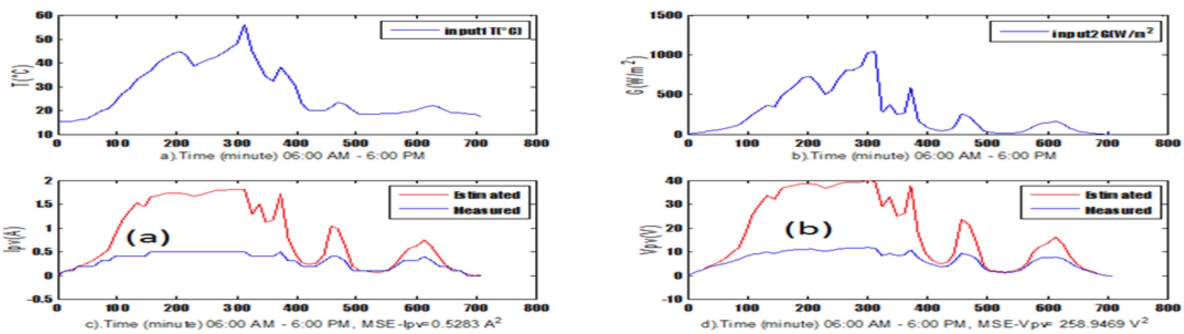

Fig. 7. PV panel performances with 50 PV cells under shading.

From all this results, we can easily conclude that the proposed monitoring system can effectively detects any power losses caused by the partial shading.

4. Conclusion

In this paper, a new intelligent method for fault detection in PV module is introduced. The case of partial shading effect is studied. The main advantage of the developed ANNBM is that doesn't require a complex system for the estimation of the photovoltaic module output power, neither a mathematical model, it can also detect any power decreasing carried out by a large types of failures that can be happened in the PV panel. This new strategy can be easily implemented in a numeric calculator using FPGA, and could also be integrated as a function for PV applications in a numeric instrument that will be our subject in the future works.

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