

Diagnosis of PV module based on neural network using performance indices

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ABSTRACT

Solar energy is an inexhaustible and clean renewable energy. Its exploitation through photovoltaic panels is clearly increasing in the world as ecologic energy. But like the conventional power grids, this new green energy could be affected by several defects that could reduce its performance, cause negative economic and safety impacts. These faults are multiple and of different natures. their consequences are based on their dangerousness. They can cause malfunction, power reduction and even total shutdown of the PV. The goal of this contribution is to implement an artificial method based on the ANN to diagnose the faults of the solar modules and to study the interest of the performance indices for the interpretation of the results of the diagnosis of the PV module. The results obtained are widely commented by different performance indices of confusion matrix and ROC curves. The neural network-based diagnostic system has a high accuracy and training was efficient because the curves of the cases are in the vicinity of unity i.e., a perfect classification.

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1. INTRODUCTION

The production of electrical energy is an index of development and a vital energy need of industrialized societies which is monotonously increasing. Also, developing countries require more electrical energy to boost their development. In view of the dangerous climate change and following the policy to fight against global warming recommended by the UN, countries are asked to switch to carbon-free energies, in this case renewable energies. There are ecologic energies as the sun, biomass, and others form of energies. In this paper we are interested in the system of photovoltaic which produces electrical energy from the sun [1]–[8]. The production of electrical energy from solar energy depends on multiple factors such as climatic conditions, electrical configurations and the various faults that could take place, and other non-critical factors [9], [10]. In practice multiple factors have been detected which contribute to increase losses such as MPPT error, losses wiring, faults such as short circuit and open circuit faults, ageing of materials [11]. The detection and diagnosis of faults in PV systems are vital for the safe operation of the PV plant for the continuity of the service [12]–[18]. In this paper is to present a method using ANN [13]–[18] for diagnosing faults in the system. It is able to detect faults that occur as PV modules, bypass diodes and short-circuit. Also, the contribution gives a numerical interpretation of the results obtained by using several performance indices and a detailed analysis of the confusion matrix.

2. MODELING PHOTOVOLTAIC SYSTEM

Figure 1 shows the single diode model of the solar cell. Where, R_s series resistor, R_{sh} shunt resistor, and the equivalent circuit above can be written:

$$I_{ph} = I_d + I_{sh} + I \tag{1}$$

$$I_d = I_0 \left[\exp\left(\frac{V+R_s I}{V_t a}\right) - 1 \right] \tag{2}$$

$$I_{sh} = \left(\frac{V+R_s I}{R_{sh}}\right) \tag{3}$$

then,

$$I = I_{ph} - I_d - I_{sh} \tag{4}$$

$$I = I_{ph} - I_0 \left[\exp\left(\frac{V+R_s I}{V_t a}\right) - 1 \right] - \left(\frac{V+R_s I}{R_{sh}}\right) \tag{5}$$

where I_{ph} is the photo-current, I_d is the diode current, I_{sh} is the current in shunt resistance, I_0 is the saturation current of the diode, R_s is the resistance series cell, R_{sh} is the shunt resistance cell, a is the diode quality (or ideality) factor and V_t is the thermal voltage and it can be defined by:

$$V_t = \frac{N_s K T}{q} \tag{6}$$

where, N_s is the number of cells connected in series, K is the Boltzmann constant ($1.385410^{-23} JK^{-1}$), q is the electron's charge ($e = 1.6 \cdot 10^{-19} C$), and T is the temperature of the cell [19], [20].

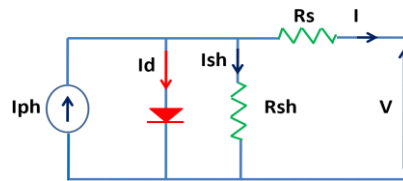


Figure 1. Equivalent circuit of a solar cell

– Photovoltaic module electrical characteristics

Diagnosis using neural networks has been tested on the SunPower SPR-X20-2506BLK photovoltaic module. Table 1 shows electrical characteristics. Figure 2 shows I-V and P-V characteristics of the PV module for two temperatures 25 °C and 45 °C.

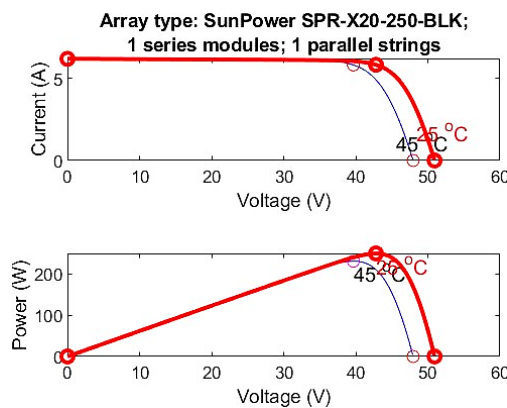


Figure 2. Electrical characteristics I-V and P-V of the SunPower SPR-X20-2506BLK

Table 1. Electrical characteristics of the SunPower SPR-X20-2506BLK

Electrical characteristics	Value
Maximum power (W)	249.952
Cells per module (Ncell)	72
Open circuit voltage Voc (V)	50.93
Short circuit current Isc (A)	6.2
Voltage at maximum power point Vmp (V)	42.8
Current at maximum power point Imp (A)	5.84

3. METHODOLOGY

Diagnosis is applied to PV system based on a string of four modules [21]–[26]. The irradiation and temperature are 1000 W/m² and 25 °C. Each PV is connected to a bypass diode. The first simulation is the healthy case and the second simulation is the faulty case with two PV modules (2 and 3) short-circuited. The outputs voltage, current and power of two simulations represent the dataset of the neural network which it is used during training. It has three inputs, voltage, current, and power of the panel with 7106 samples each, ten hidden neurons and an output of two-class with 7106 samples as shown in Figure 3.

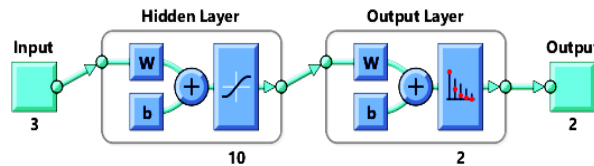


Figure 3. Design of the neural network

4. SIMULATION AND DISCUSSION

The voltage, current and power of each simulation are saved in files. With appropriate commands, the three vectors form the inputs to the neural network. The training was carried out by the scaled conjugate gradient backpropagation method. The simulation system on Figure 4 has a string with four modules, four bypass diodes. Figure 5 shows the diagnostic model based on neural networks under Simulink. It is formed by the input, the neural network and the visualization of classes. The short circuit of two modules decreased both current and power of the PV system shown in Figures 6 and 7.

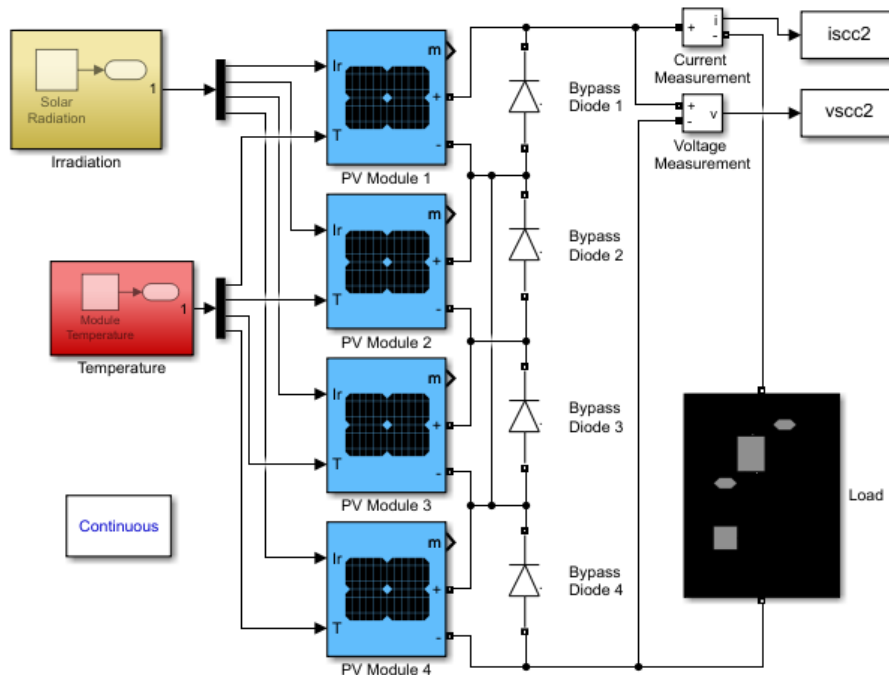


Figure 4. Simulation system

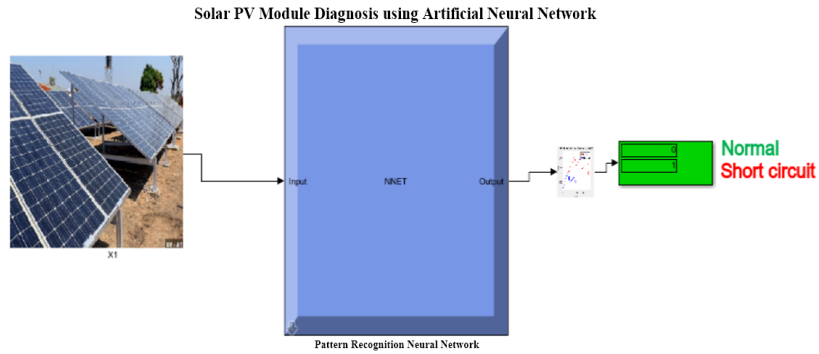


Figure 5. PV diagnostic system based on neural networks

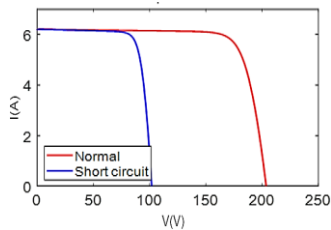


Figure 6. Electrical characteristics I-V for healthy case and faulty

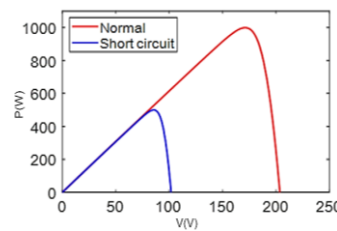


Figure 7. Electrical characteristics P-V for healthy case and faulty

Figure 8 presents the receiver operating characteristic curves which represent the sensitivity for all the possible threshold values. The sensitivity is the ability of the test to correctly detect defective cases and specificity is the ability of the test to correctly detect healthy cases. According to Figures 8 and 9, the proposed diagnostic system has a high accuracy and training was efficient because the curves of the cases are in the vicinity of unity i.e., a perfect classification.

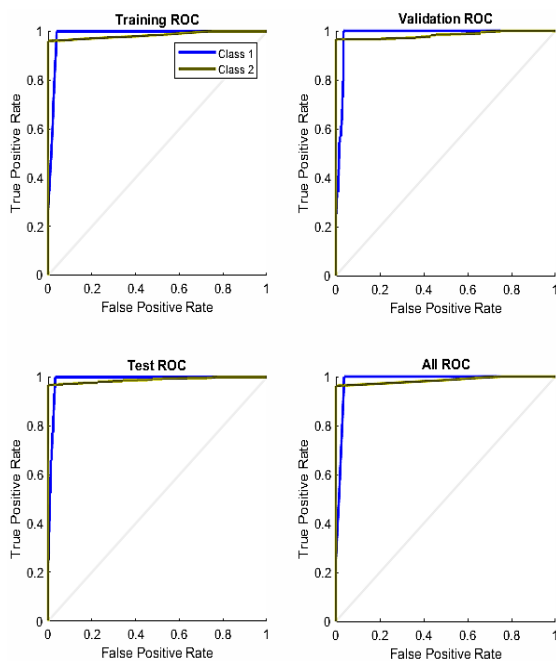


Figure 8. Receiver operating characteristic curves

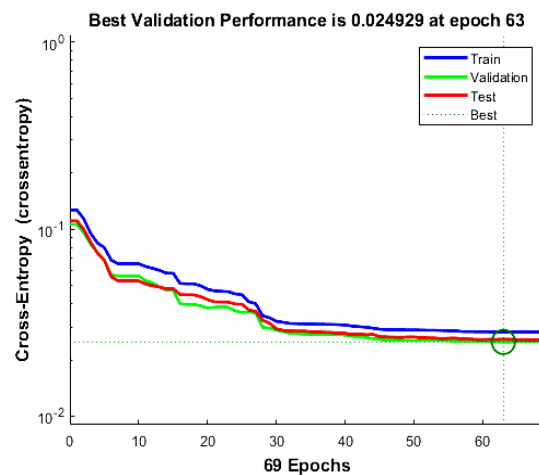


Figure 9. Performance

Figure 10, the diagonal cells indicate the number and percentage of correct classification. For example, 143 cases are correctly classified as normal. This corresponds to 2.0% of the total. Similarly, 6706 cases are correctly classified as short-circuit. This corresponds to 94.4% of the total. While, 66 short-circuit cases are wrongly classified as normal and this corresponds to 0.9% of the total. Similarly, 191 normal cases are wrongly classified as short circuit and this corresponds to 2.7% of the total. To explain and analyze the results of the confusion matrix, it is necessary to use different performance indices which are presented below:

- Positive (P): the number of real positive cases (short-circuit).

$$P = TP + FN$$

- Negative (N): the number of real positive cases (normal).

$$N = TN + FP$$

$$Total = P + N$$

- True positive (TP): indicates correctly that the short circuit is present.
- False positive (FP): indicates wrongly that the short circuit is present.
- True negative (TN): indicates correctly that the short circuit is absent.
- False negative (FN): indicates wrongly that the short circuit is absent.

$$TP=6706 \text{ and } FP=191$$

$$TN=143 \text{ and } FN=66$$

- Incidence rate

$$\frac{TP}{Total} = \frac{6706}{7106} = 94.4\%$$

- Prevalence

$$\frac{P}{Total} = \frac{6772}{7106} = 95.3\%$$

- Specificity: the proportion of negative cases correctly predicted.

$$\frac{TN}{TN + FP} = \frac{143}{143 + 191} = 42.8\%$$

- False positive rate

$$\frac{FP}{TN + FP} = \frac{191}{143 + 191} = 57.2\%$$

- False negative rate

$$\frac{FN}{FN + TP} = \frac{66}{143 + 6706} = 1.0\%$$

- Sensitivity: the proportion of positive cases correctly predicted.

$$\frac{TP}{FN + TP} = \frac{6706}{66 + 6706} = 99.0\%$$

- Negative predictive value: the true negatives in the total of negative predictions.

$$\frac{TN}{TN + FN} = \frac{143}{143 + 66} = 68.4\%$$

- False omission rate

$$\frac{FN}{TN + FN} = \frac{66}{143 + 66} = 31.6\%$$

- False discovery rate

$$\frac{FP}{FP + TP} = \frac{191}{191 + 6706} = 2.8\%$$

- Positive predictive value (precision): the true positive in the total of positive predictions.

$$\frac{TP}{FP + TP} = \frac{6706}{191 + 6706} = 97.2\%$$

- Accuracy: the proportion of correctly classified observations.

$$\frac{TP + TN}{Total} = \frac{6706 + 143}{7106} = 96.4\%$$

- Balanced accuracy:

$$\frac{Sensitivity + Specificity}{2} = \frac{0.99 + 0.428}{2} = 70.2\%$$

- Misclassification rate

$$\frac{FN + FP}{Total} = \frac{66 + 191}{7106} = 3.6\%$$

$$F1_{score} = \frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2 \times 0.972 \times 0.99}{0.972 + 0.99} = 98\%$$

As we can see, the performance indices are multiple and complementary. They allow us to carry out a quantitative and qualitative analysis of the diagnosis of the PV panel. To analyze the performance of our PV module diagnostic model based on neural networks, we calculated accuracy (true positives and true negatives are more important) and the F1_Score (false negatives and false positives are critical) which are respectively 96.4% and 98%.

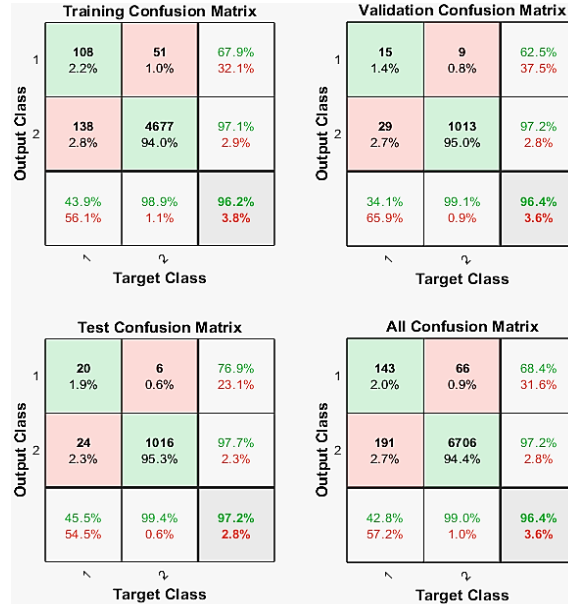


Figure 10. Confusion matrix

5. CONCLUSION

Simulation study is carried out for the diagnosis of a PV module with two classes by neural networks. In addition to the diagnosis, we were interested in the various performance indices which are multiple, complementary and allow us to give a scientific analyze of the results. The intelligent diagnostic system classified the inputs with a high accuracy. Therefore, neural networks are a very powerful and very suitable intelligent technique for the diagnosis of photovoltaic systems.




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