Artificial Neural Network-Based Classifier for Fault Detection in Photovoltaic Modules

Kritika Anuragi, Mohak Gaba, Ashir Raza Malik, Ritwik Gambhir, and Bhavnesh Kumar

Abstract The widespread use of solar energy today highlights the importance of maintaining the performance characteristics as well as optimizing the efficiency of photovoltaic (PV) system installations. PV system performances are often lost due to several factors such as shading (uniform or partial), breakage or cracks and creation of hot spots. Such faults can also sometimes result in glass breakage, cell degradation and permanent damage to the PV module. Numerous parameters must be constantly monitored to ensure that any abnormal losses and faults ensuing on the PV module are detected timely. Many monitoring systems in the industry are based on the monitoring of temperature, solar irradiance, variable resistance, direct current and voltage. In this paper, a fault detection method for PV modules has been described. It consists of using a classifier based on artificial neural network (ANN) that estimates the generated output (photovoltaic current and photovoltaic voltage) under variable input conditions. The input (solar irradiation, temperature and variable load) and output (current and voltage) data measured over a period of six weeks has been used for the development of the ANN-based classifier. The differences between the estimated values of current and voltage generated by the ANN and the measured values generated from the physical setup are used to predict the operating state of the photovoltaic module. The results showed that this method, which uses only two meteorological conditions, accurately detects the operating state as normal (un-shaded condition) or faulty (shaded condition) of the photovoltaic module.

Keywords Fault classifier · Photovoltaic module · Artificial neural network · Partial shading

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1 Introduction

A photovoltaic (PV) system consists of one or more solar panels that utilize sunlight as an energy source to generate electricity. Today, such photovoltaic systems play a crucial role in electrical power applications and are being widely used for commercial and residential purposes. The widespread use of solar energy in the present day underlines the requirement for optimizing the efficiency of PV installations and developing effective monitoring systems for maintaining the performance of PV systems [1]. Monitoring systems should be equipped to continuously follow the PV system's operating state. This is essential for early detection of errors and failures that trigger performance losses. Shading, hot spotting [2] and cell shunting [3] are few major factors that severely affect PV performances. To mitigate the aforementioned problems, monitoring systems use meteorological parameters such as temperature and solar irradiance as well as output parameters like current and voltage.

Many existing methods of fault detection use plant function data collected over a period of time to monitor the operating state and detect abnormalities and faults, i.e., they operate offline only [4]. Some other techniques that were developed required complex mathematical calculations to predict faulty parameters [5]. Most of these methods did not estimate the system's real operating state and were mostly based upon analysis of system performances and I-V curve measurements [6]. These techniques fail to give real operation state in peculiar cases such as that of partial shading. All these methods involve tedious calculations and complex analysis for determination of the operating state of PV installations.

Artificial intelligence techniques are slowly penetrating every field of research, and the same is true for the photovoltaic field where ANNs are being successfully employed in multiple ways such as health monitoring [7, 8], maximum power point tracking [9–11], solar forecasting [12] and modeling and simulation.

In this paper, a fault detection method for PV modules has been described that employs ANN algorithms in the developed classifier. ANN generated estimated values of output current and voltage under variable input conditions (temperature, solar irradiance and variable resistive load). This method enables real-time fault detection. The introduced method is independent of PV module performances. The difference between the predicted values of voltage and current generated by the ANN and the measured values generated from the physical setup is used to detect the operation state. This method allows us to avoid complex calculations and intensive analysis of system performances. Thus, the method is autonomous and will always be able to conclude the operation state of the module as normal (un-shaded condition) or faulty (shaded condition).

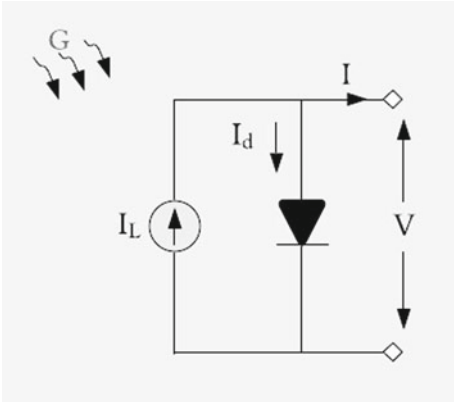


Fig. 1 Equivalent circuit of a PN junction PV cell

2 System Description

2.1 Equivalent Model of a PV Cell

An ideal PV cell can be visualized to be a current source, wherein the current produced by the cell is directly proportional to the light intensity being received by the cell. An equivalent model of the PV cell can be obtained by adding appropriate components, which will show the electrical and optical losses of the PV cell with an ideal current source.

$$I = I_{\mathrm{L}} - I_{\mathrm{d}} \tag{1}$$

$$I_{\mathrm{d}} = I_{\mathrm{o}}\left(e^{\frac{qV}{nkT}} - 1\right) \tag{2}$$

Figure 1 illustrates the single-diode model for a PV cell. I_{L} is the light-generated current, I_{D} is the current that passes through the diode, whereas I and V are the PV cell current and voltage, respectively. Optical losses are represented by the current source as illustrated in the electrical circuit shown in Fig. 1. In this single-diode model, the diode represents the loss which results from recombination in base and emitter region.

2.2 I-V Characteristics of a PV Cell

PV cells are characterized and compared with each other using short-circuit current, open-circuit voltage and fill factor. The aforementioned parameters are represented in the I-V curve of PV cell shown in Fig. 2.

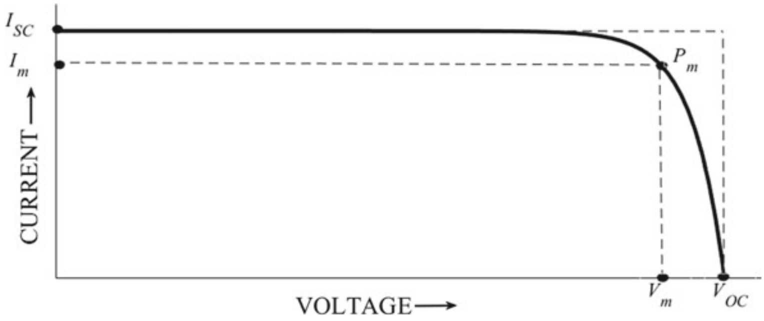


Fig. 2 Typical I-V characteristics of a PV cell

Short-circuit current, I_{SC}, is nothing but the maximum current that flows in a solar cell when both the P-terminal and N-terminal are short-circuited with each other, and hence, V is zero. Putting $V = 0$ in given equation, we will get $I_{SC} = I_L$. Thus, the short circuit is nothing else but the light-generated current, I_L. Open-circuit voltage, V_{OC}, is defined as the maximum voltage that is produced across the terminals of a solar cell when the circuit is kept open that is $I = 0$. Putting the above conditions in the equation of current, we will get the following expression for open-circuit voltage:

$$V_{OC} = \frac{nkT}{q} \ln\left(\frac{I_L}{I_O} + 1\right) \tag{3}$$

Thus, V_{OC} depends on the reverse saturation current and light-generated current.

3 Materials and Methodology

The proposed solution for fault detection of PV module involved the use of artificial neural network. The ANN was trained using actual data collected by a physical setup using a solar panel. This trained neural network further gives estimated values of the output current and voltage for the given input parameters. The difference between the estimated and the measured values is the basis of classification.

3.1 Database Generation Using PV Panel

The data was measured using a Loom Solar 20 W–12 V PV module at Netaji Subhas University of Technology.

A dataset of 4000 + vectors was generated over a period of six weeks. The datasets were then divided into two subsets—70% of the samples were used for training of

Table 1 Specifications for Loom Solar 20 W–12 V solar panel at STC

Maximum Power, P_m	20 W
Maximum Power Voltage, V_m	19.25 V
Maximum Power Current, I_m	1.04 A
Short-circuit Current, I_{SC}	1.11 A
Open-circuit Voltage, V_{OC}	22.50 V

the neural network, and 30% of samples were used for testing and validation. Table 1 gives the specifications of the PV module used for generating the training data.

3.2 Experimental Setup

The physical setup for data collection basically involved a PV panel being connected to a variable load. Different sets of readings were taken at variable timings to incorporate a wide range of input temperatures (T) and irradiance (G). The output values of photovoltaic current (I_{PV}) and photovoltaic voltage (V_{PV}) were measured across a rheostat with resistance values ranging from 1 to 5000 Ω. The data generated for training was measured under temperatures ranging from 20 to 40 °C and irradiance ranging from 70 to 1200 W/m^2. Figure 3 illustrates the process of data generation using experimental setup.

Multiple sets of readings were generated at varying input conditions of temperature and irradiance. The data points for each set were plotted to obtain a trend line.

All these graphs closely resembled the characteristic I-V curve of a PV cell, which reiterated the accuracy of the readings. The trend lines were used to obtain the equations for each reading. These equations were further used to obtain more

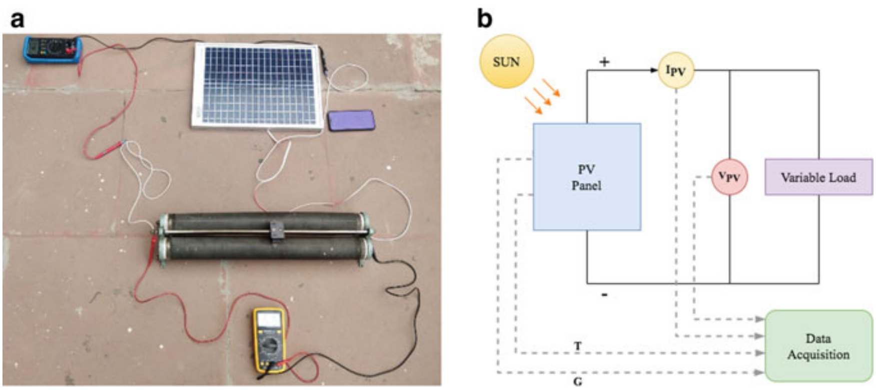


Fig. 3 Data generation: **a** Experimental setup. **b** Block diagram representation

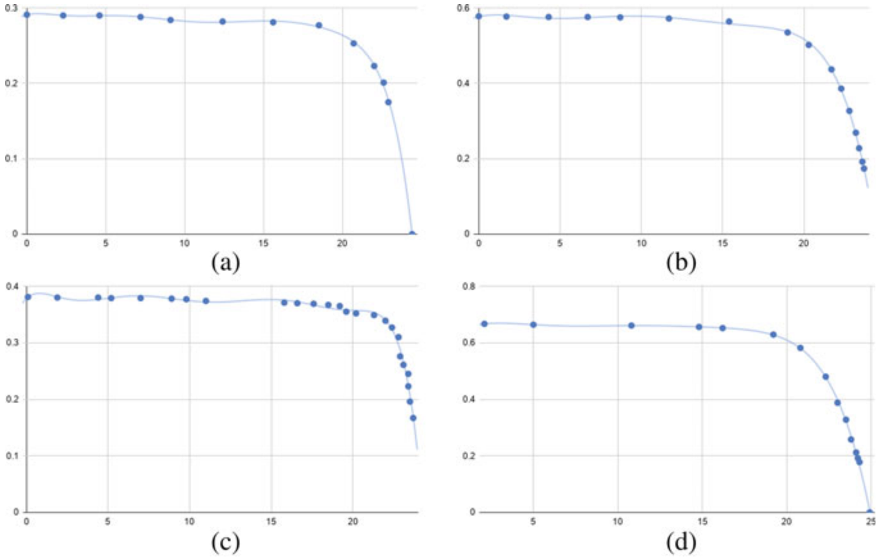


Fig. 4 Current–voltage curves for **a** $T = 29$ °C and $G = 72.68$ W/m^2. **b** $T = 26$ °C and $G = 143.78$ W/m^2. **c** $T = 28$ °C and $G = 148.52$ W/m^2. **d** $T = 29$ °C and $G = 289.14$ W/m^2 (X-axis: Voltage (V), Y-axis: Current (A))

datasets for a given value of temperature and irradiance for varying load values. Some of the graphs obtained have been shown in Fig. 4 (voltage across X-axis and current across Y-axis).

4 Proposed ANN Classifier

Temperature, irradiance and load values were fed to the input layer for training the network as shown in Fig. 5. Every input into the network is further fed to the nodes in hidden layer. ANN uses input values, modification is done by multiplying the input values with the weight value, these new values are added up and sent to the activation

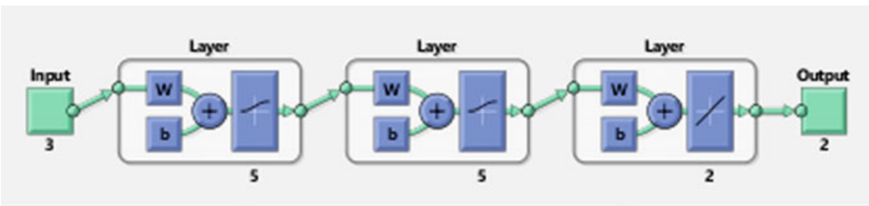
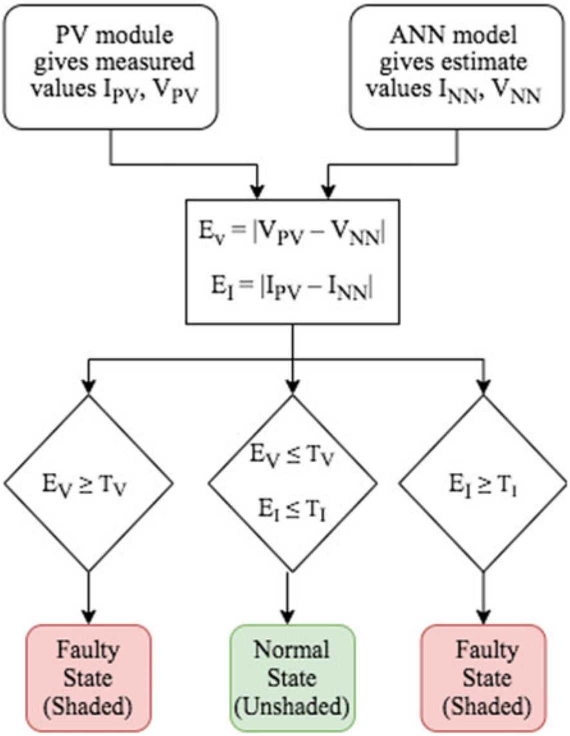


Fig. 5 Proposed multilayer perceptron structure

function in the hidden layers, and the output from the hidden layers now becomes the input for the next hidden layer (if present), otherwise for the output layer. Different activation functions along with varying combinations of number of hidden layers as well as number of neurons in hidden layers were used to obtain best results. Primarily, resilient back propagation (RPPROP) algorithm and Levenberg–Marquardt (LM) algorithm were used.

Figure 6 illustrates the working of the classifier. The trained neural network generates estimate values of output current and voltage when input values of temperature, irradiance and resistance are fed to the neural network. Further, output measurements are also obtained for the same input from the physical system. If the error between the measured and estimated values, E_V and E_I, both falls under acceptable error threshold values, T_V and T_I, then the operation of PV module is classified as normal (un-shaded condition). In all other cases, the operation state of PV module is classified as faulty (shaded condition).

Fig. 6 Classifier flowchart



5 Results and Discussion

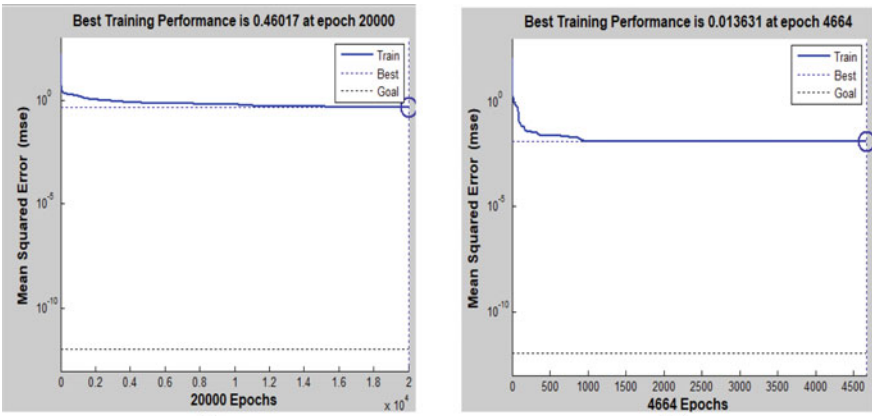
It was observed that different training algorithms provided different results as described in Table 2 and the training performance is illustrated in Figs. 7 and 8. It was also observed that varying the number of hidden layers or the number of neurons also altered the training results.

The panel was manually shaded to obtain results from the classifier under varying conditions of faulty operations. The values were measured at input conditions of irradiance (G) = 130 W/m^2, temperature (T) = 20 °C and resistance load (R) = 80 Ω. The obtained classifier results are recorded in Table 3.

It was observed that the classifier produces satisfactory results. This comparison-based classifier model has multifaceted applications in daily life. It is necessary to study the real-time operation states of the PV module. This fault detection classifier aims to avoid critical damage to the PV module by timely detection of faulty operation under shaded conditions.

Table 2 Training results from different algorithms

Algorithm	Best training performance
Resilient back propagation	0.46017
Levenberg–Marquardt	0.013631



(a) (b)

Fig. 7 Performance and MSE curve for: **a** RPROP, **b** LM

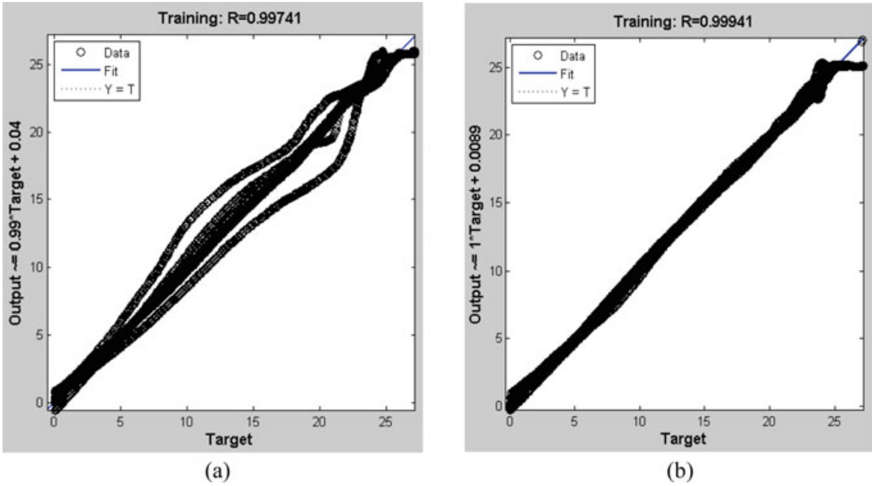


Fig. 8 Regression curve for: **a** RPROP, **b** LM

Table 3 Classifier outputs for different shading conditions

Parameter	Values		
	During no-shading	During 25% shading	During 50% shading
V_{PV} (V)	24.124	10.63	5.12
I_{PV} (A)	0.3102	0.1265	0.0621
V_{NN} (V)	23.0456	23.0456	23.0456
I_{NN} (A)	0.2981	0.2981	0.2981
E_V (V)	1.074	12.4156	17.92
E_I (A)	0.0121	0.1716	0.236
T_V (V)	2.3	2.3	2.3
T_I (A)	0.02981	0.02981	0.02981
$E_V \leq T_V$	Yes	No	No
$E_I \leq T_I$	Yes	No	No
Result	Normal (Un-shaded)	Faulty (Shaded)	Faulty (Shaded)

6 Conclusion

It can be concluded that after gathering physical data split over several readings, a neural network based on a Levenberg–Marquardt learning paradigm is more suitable for approximating the I-V characteristics of a solar panel, when compared to a resilient back propagation network and other training paradigms. This trained artificial neural network is a key aspect of the developed classifier which can be used to identify if a solar panel is working in faulty state (shaded condition) or normal state (un-shaded condition). Real-time detection of the PV module's operating state is crucial in order to prevent damages and losses due to faults. Once the operating state of the panel has been identified by the classifier, this information can be further used to determine the nature and extent of the fault as well as develop appropriate mitigation and prevention strategies.

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