Photovoltaic Faults Prediction by Neural Networks

M. Santhosh, P. Bhargav, and Arun Balodi

Abstract Solar energy is one of the most important forms of renewable energy. The most significant method of converting solar energy is photovoltaic (PV) systems. Fault diagnosis is crucial for the dependable and efficient operation of PV systems. Early fault detection and diagnosis can save maintenance costs, avoid or minimise system downtime, and generally improve system performance. Artificial neural networks, a key artificial intelligence methodology, have been developed and applied in a variety of fields, including the fault diagnosis of PV systems, because of their robust self-learning capability, outstanding generalisation performance, and high fault tolerance. This study shows how artificial neural networks (ANN) can be used to predict solar panel problems.

Keywords Artificial intelligence · Fault diagnosis · Artificial neural network · Photovoltaic · Solar energy

1 Introduction

An energy revolution is currently taking place in modern society in an effort to switch from fossil fuels to renewable energy sources in order to stop catastrophic climate change [1]. The development of urban areas and technological advancements nearby should strongly encourage the use of renewable energy sources. As a result, the demand for renewable energy is rising daily [2]. Solar photovoltaic (PV) energy has quickly replaced conventional energy sources in recent decades due to its global availability, modularity, lack of pollution, ease of installation, and low cost. Particularly in terms of efficiency, affordability, and optimising the power that can be collected from PV cells, the study of PV systems has evolved tremendously. Never-

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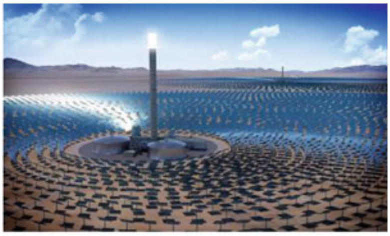
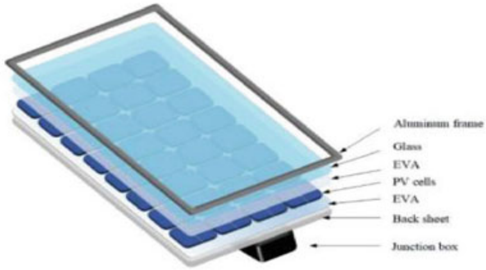
(a) The solar panel



(b) Concentrating solar thermal power



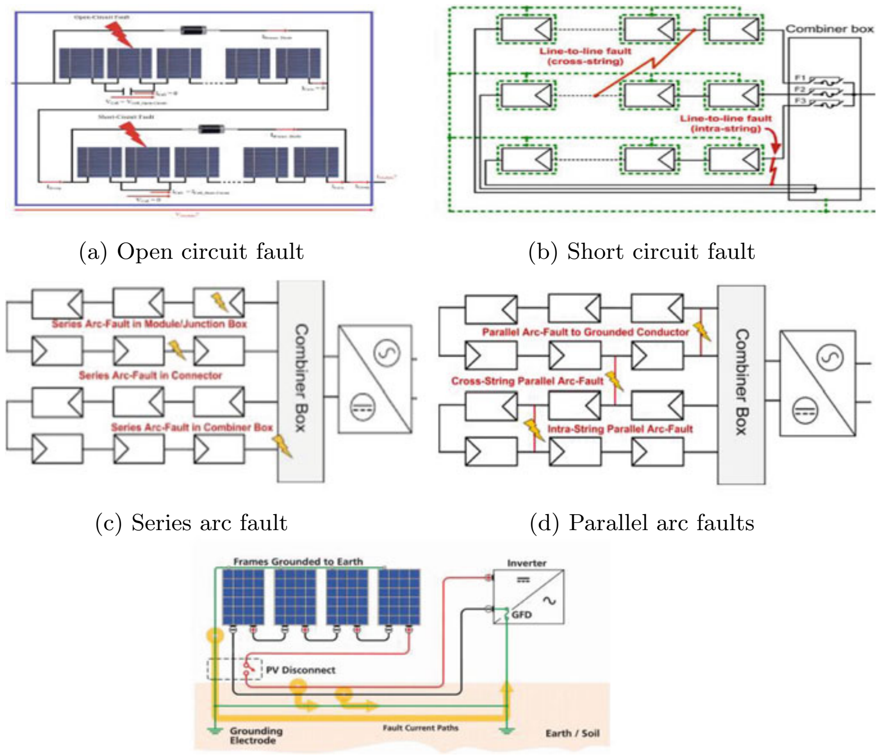
(c) Solar Panel

Fig. 1 Solar plant and solar panel

theless, a variety of faults frequently affect PV systems, which can negatively impact their conversion efficiency and safe operation [3].

The solar panels in large areas produce high energy but when these solar panels are getting aged faults will be occurring in every solar panel. It is a difficult problem to identify in which solar panel faults are occurring. The faults in the solar panel make a solar panel give less energy. The faults in a solar panel damage the entire solar panel. After the damage to a solar panel, the full solar panel has to change [9]. To increase the efficiency of solar panels many methods came like MPPT (maximum power point tracking) [6], using SMD (smart monitoring devices) [7], and using many algorithm methods, etc. (Fig. 1).

There are three different categories of failures in PV systems: electrical, chemical, and physical faults [10]. Therefore, experts have proposed a range of strategies to quickly and accurately identify and diagnose a variety of faults in PV systems. The two primary categories of defect diagnosis procedures are the electrical approach and the thermal and optical methods [11]. Open circuit faults, line-to-line faults (short circuit), arc faults (series and parallel), ground faults, bridging faults, dust (soil formation), and cell-level degradation (quality control) are common defects that affect all solar panels [8]. The open circuit fault is the disconnection of the current from all the solar panels associated with the same string zero. The detection methods used for the open circuit faults are analysed based on measured ambient conditions, current, voltage, etc. For small-scale plants, optical and thermal methods



(a) Open circuit fault

(b) Short circuit fault

(c) Series arc fault

(d) Parallel arc faults

(e) Ground faults

Fig. 2 Different faults in solar panel

are sufficient for fault monitoring and diagnosis, whereas electric methods are better suited for PV system monitoring and diagnosis [12].

Line-to-line faults develop when connections made between two sites of difference in an electric network or system have unintentionally low resistance. The method used for the line-to-line faults is an analysis based on the ambient conditions, current, voltage, etc. The line-to-line faults in a solar panel are also identified as short circuit faults (Fig. 2).

The arc faults are divided into two categories they are series arc faults and parallel arc faults. Series arc faults are formed due to a loss of the continuity of a conductor, connection, module, or other PV system components. The detection methods are the current and voltage measurement and frequency domain analysis of a PV array current. But the parallel arc faults are between the two conductors or between the conductor and the ground. Frequency domain analysis of a current and the detection of a sharp reduction in the PV array's voltage or current are the two methods used to find parallel arc defects.

The ground faults are formed because of the accidental electrical short circuit involving the ground and one or more normally designated current-carrying conductors. The methods used for detection are frequency current measurement, reflectometry, and current and voltage measurement [10].

The other types of faults like dust on the solar panel can reduce 30% of output in one month. So, the solar panels have to clean daily for better and clean output. The methods are using for to detect dust on the solar panel are thermography and visual inspection. And one more fault in the solar panel is cell-level degradation. The high quality of the solar panels is degraded at a rate of around 0.5% every year generating around 12–15% less power. To detect this degradation, fault a technique is used called different imaging techniques.

Artificial neural networks are the one of most growing technologies in the present generation. By using this technology can identify all the types of faults in solar panels. One of the greatest things about the ANN it not only identifies faults it also shows which type of fault in the solar panel. Using this ANN can predict the faults in the solar before the faults are getting bigger. The implementation of ANN will be shown in the methodology [13–15].

The remainder of this paper is organised as follows: The problem statements are covered in Sect. 2. The methodology for PV system defect diagnostics is introduced in Sect. 3. Results are discussed in Sect. 4. This work's conclusion and its possibilities are presented in Sect. 5.

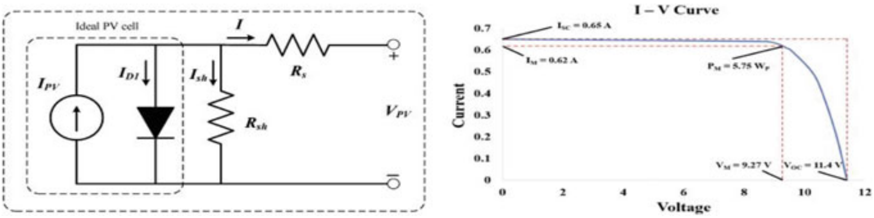
2 Problem Statement

This research focuses on the use of ANN for solar PV system fault detection. With the help of ANN technology, machines, and computers can become intelligent on their own. ANN has nodes in it called Neurons. An ANN is composed of three layers: the input layer, the output layer, and the hidden layer [4, 5]. Through the use of an activation function, the hidden layer generates output from a set of weighted inputs. Multiple input layers, multiple output layers, and numerous hidden levels are also possible with ANN.

3 Methodology

The solar panel of a PV cell forms nonlinear I- V characteristics and it can be obtained by a simple model which consists of a constant current source, diode, and a resistor associated in both the series and in the parallel.

Typically, the electrical behaviour of a solar cell is described using the PV module of one diode and two diodes models. Figure 3b roughly depicts the equivalent circuit of a photovoltaic cell (PV). Several factors affect how sunlight is converted into electricity. Table 1 lists these factors.



(a) PV module (b) I-V characteristic

Fig. 3 PV module and I-V characteristic

Table 1 PV parameters

Amps	Volts	Watts
0	Voc = 11.4	0
0.2	11.06	2.21
0.4	10.59	4.24
0.5	10.24	5.12
0.6	9.54	5.72
0.61	9.39	5.73
$I_M = 0.62$	$V_M = 9.27$	$P_M = 5.75$
0.63	9.08	5.72
0.64	8.72	5.58
$I_{SC} = 0.65$	0	0

In Table 1 and graph, the major parameters are identified as the current, voltage irradiance, and temperature. If there is a change in any parameter there will be a change in the output also. The STC (standard test conditions) manufacturers provide the cell parameters. The comparable solar radiation under the STC is 1000 W/m^2. The working temperature of the cell is 25 °C. Maximum power point (MPP), is the working peak of each solar panel. The fault detection using I-V data can be accomplished by measuring MPPs and observing the variation of a measured MPP from an actual MPP. The unsupervised algorithm was ineligible to be categorised as a defect. Therefore, in order to categorise unlabeled data, we need a method that is also employed for partially labelled data. Using artificial neural networks (ANN), we are able to accurately identify the type of fault as well as detect it. Use MATLAB software for the code and SIMULINK as described in Fig. 4 to implement and understand how ANNs in solar panels work.

To implement ANN model the following steps are involved.

1. Selecting of inputs and targets.
2. Validation of the data set.
3. Deciding the number of hidden Neurons.
4. Training the network by using any training algorithm.
5. Network testing.

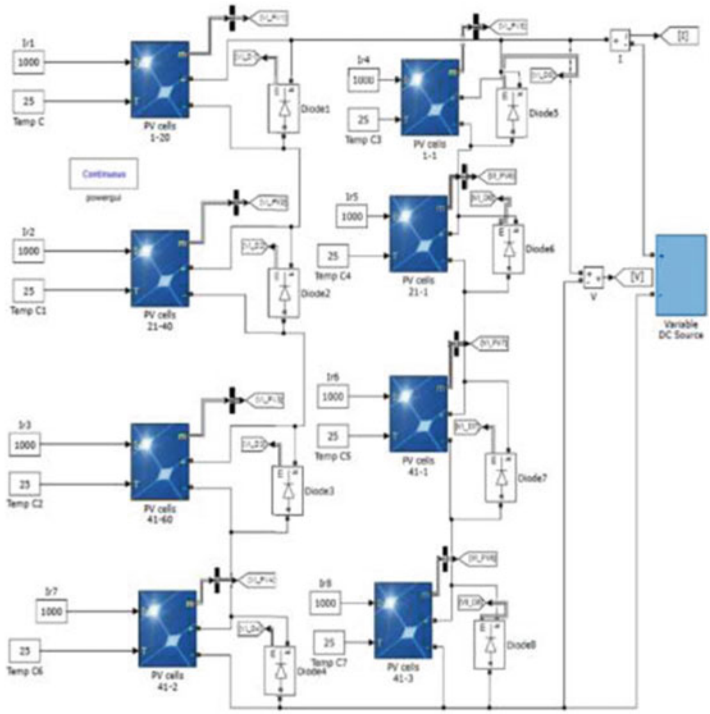


Fig. 4 I-V characteristic

To implement the ANN we have to collect the data from the solar panel. And we know the important parameters of the solar panel. To build the ANN the data has to be trained for the detection and for identifying the faults. The collection of data is a major thing for ANN. The collected data of the different parameters will be collected as the maximum data and minimum data as shown in Table 2.

3.1 Building Model

Data from the solar panels should be gathered in order to create the ANN Model. To forecast the errors, the data should be trained using the obtained data. The dataset is divided into 7 layers ranging in value from x_1 to x_7 for an input layer of an ANN. The current (A) in branch 1 of the PV system is x_1, while branch 2's current (A) is x_2. In the PV system, branch 1 has a voltage of x_3 while branch 2 has a value of x_4. The irradiation level (k lux) is x_5. The average temperature of the PV system is x_6. The weather is represented by the integer x_7 (snow, sunny, overcast, rainy). Two hidden layers, h_1 and h_2, combine to form the hidden layer. We select the ReLU

Table 2 Sensor data

State		SI1	SI2	Sv1	Sv2	Irradiation klux	Temperature	Weather
		Amps		Volts				
Normal	Max	7.6		110		110	41	Sunny/summer
		5.4		102		97	23	Cloudy/summer
	Min	5.5		105		108	15	Sunny/winter
		0.4		80		9	−3	Cloudy/winter
Open	Max	7.6		110		108	15	Sunny/winter
	Min	0		0		9	−3	Cloudy/winter
Line-line	Max	6.1		90		110	41	Sunny/summer
		1.8		72		97	23	Cloudy/summer
	Min	5.5		75		108	15	Sunny/winter
		0.4		62		9	−3	Cloudy/winter
Variance		0.52		7.23		35.56	8.7	Summer
		4.82		9.54		47.61	15.24	Winter

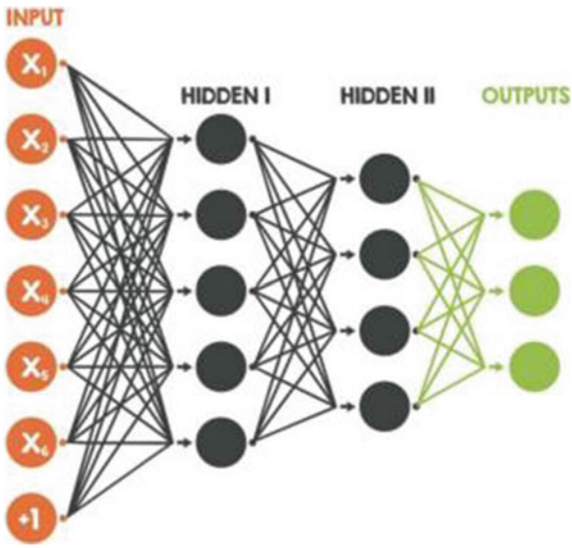


Fig. 5 Layers of ANN

(rectified linear unit) as the activation function since it offers several benefits in multidimensional nonlinear datasets. According to the ReLU, $y = max(0, x)$. The three layers y_1, y_2, and y_3 make up the output layer. To create the ANN model for defect detection, the various parameter data sets that have been collected will go through the following processes. The multilayer perceptron (MLP), which has a backward network and a feedforward network, is depicted in Fig. 5. The ANN module learns a lot from the trained data, and the output is compared to the tested data.

Fig. 6 Flow chart of the fault detection

Table 3 I-V characteristic

	Time	Ipv	Vpv	Vdc	ia	ib	ic	va
0	0.000041	2.369843	90.429688	147.949219	0.616820	−0.530396	−0.160283	−146.003418
1	0.010040	2.378357	90.368652	148.242188	−0.678956	0.570679	0.047847	148.546906
2	0.020039	2.373627	90.460205	148.535156	0.603393	−0.537109	−0.187139	−145.027008
3	0.030038	2.368896	90.423584	148.242188	−0.685670	0.570679	0.041133	147.341461
4	0.040037	2.362274	90.435791	148.242188	0.630248	−0.523682	−0.166997	−143.279114

	vb	vc	Iabc	If	Vabc	Vf	Label
0	120.255127	25.595601	1.000000	50.000000	1.000000	50.000000	FOM
1	−119.881439	−24.723663	1.000000	50.000000	1.000000	50.000000	FOM
2	120.315399	26.109924	1.000000	50.000000	1.000000	50.00000	FOM
3	−119.736789	−26.105906	0.440380	50.078491	118.275197	49.921509	FOM
4	120.942230	26.680501	0.618996	50.248673	90.022162	49.606494	FOM

Machine Learning (ML) error identification and diagnosis methods have been used recently. The training data determines how effective the ML technique is. The training data and PV data typically have very high prediction accuracy rates that can reach 100%. Finding the key features of the input dataset is of the utmost importance for the ML system while building an ML model.

Figure 6 shows the steps of the code for fault detection. Collect the data of the parameters like temperature, voltage, current, and irradiance. Import the data by spitting the data into 70 and 30%. 70% of the data is used to train the system and the remaining of 30% of the data is used for the test data. After training the ANN with the data the ANN module will be builded. Then the predictions will of the form of confusion matrix. The data of all the parameters are taken in the two forms like minimum dataset and maximum dataset in different conditions of the weather. For to predict and to build the ANN module with the knowledge the sample data is given which is shown in Fig. 7. This sample data helps the ANN module to predict and identify the faults by comparing the values. And the ANN module is trained with large datasets containing different data values as shown in Table 3.

Each data column is described as the following: Time: The time of real measurement in seconds. The avg sampling is $T_s = 9.9989$ Ms. Ipv: PV array current measurement. $V_{p}v$: PV array voltage measurement. $V_{d}c$: DC voltage measurement. i_a: Phase-A current measurement. i_b: Phase-B current measurement. i_c: Phase-C current measurement. v_a: Phase-A voltage measurement. v_b: Phase-B voltage measurement. v_c: Phase-C voltage measurement. $I_{a}bc$: Positive- sequence estimated current magnitude. I_f: Positive- sequence estimated current frequency. $V_{a}bc$: Positive- sequence estimated voltage magnitude. V_f: Positive- sequence estimated current frequency.

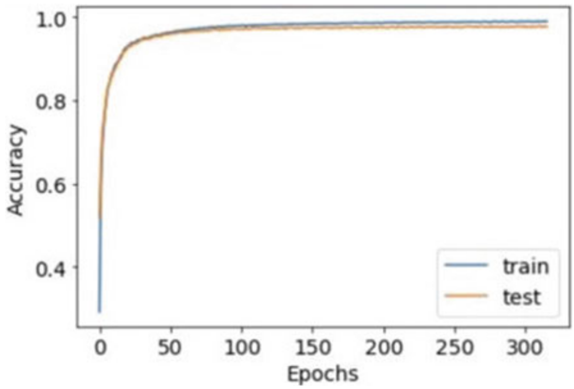


Fig. 7 Accuracy versus Epochs curve

There are other parameters also like the temperature and the irradiance which are given in the solar panel.

4 Results

In an ANN, data travels in two directions: forward propagation and the MLP, which forecasts results for the input dataset. Back propagation also takes the mistake in the projected data into account while adjusting its settings. The graph of the trained and tested data is shown in Fig. 7. A complete iteration of the algorithm over the training data set is referred to as an epoch. Each epoch consists of one or more batches where we train the neural networks using a portion of the dataset. The epoch aids in identifying the model from the data.

Which model is most effective at recognising the connections and patterns in the trained data depends on its accuracy. The ratio between the correct prediction data sets and the overall number of predictions in the trained datasets is predicted by the epoch and accuracy graphs. The precision of a PV cell is not increased by increasing the epochs. The confusion matrix, which is displayed in Fig. 8, compares the trained data's predictions to the tested data. The confusion matrix displays all datasets with insufficient data as well as the most datasets possible. Checking the data's accuracy is necessary.

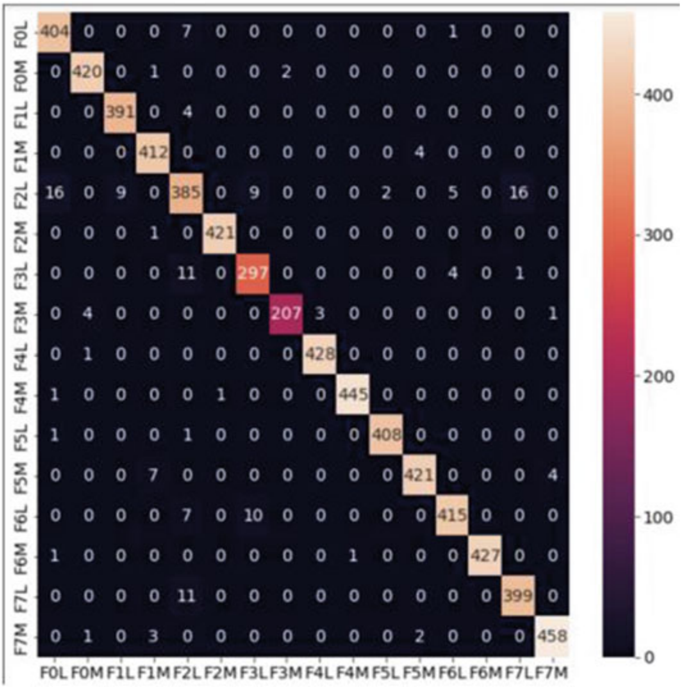


Fig. 8 Confusion matrix

5 Conclusion

The basics of various PV panel failures were explored in this study. The current ANN-based fault detection and diagnostic techniques were tested in trials. The simulation results using neural networks are successfully displayed by recognising and detecting frequently recurring defects. It shows a significant improvement in detection precision. It is quite efficient to utilise ANN to predict and locate problems in or between PV modules. The existing fault diagnosis ANNs face a serious problem with the cost of training time. These ANNs can be employed in conjunction with an embedded system of digital signals to provide real-time diagnostics, maximising the effectiveness of the fault diagnosis system. It is intended to employ this problem detection in massive PV systems in the future.

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