



# Solar PV Fault Classification using Back Propagation Neural Network

Poonam Shinde, S. R. Deore

**Abstract:** Solar energy is that the foremost abundant, inexhaustible and clean of all renewable energy resources. Interest in electrical solar PV power generation has accumulated in recent years due to its benefits. This wide distribution of physical phenomenon panel production wasn't followed by watching, fault detection and designation functions to verify higher gain. In this paper, real time fault analysis and fault detection is done by using Back propagation. By simulating various fault conditions, the performances of a faulty electrical solar photovoltaic module have been compared with respect to its faultless model by quantifying the precise differential residue which can be associated with it. The deformations and faults induced on the I-V curves and P-V curves have been studied to generate data for neural network analysis for different types of faults. Five different fault cases like module to module fault, module - ground faults, short circuit fault, and different shading patterns of modules and solar cells are considered. The MATLAB simulation model's results show the respective results for various fault conditions along with variation of different solar irradiation which commonly occur in the photovoltaic systems. The projected technique is often generalized and extended to additional sorts of faults. This faults condition was analyzed by using Backpropagation Based Neural Network (BP-ANN). Back propagation technique ensures fine tuning the weights of neural network to get lower error rates making the model more reliable, therefore the BP-ANN technique contributes in improving the overall accuracy for fault detection in the system using Artificial Neural Network.

**Keywords:** Neural Network, Solar PV system faults, fault detection, Back propagation.

## I. INTRODUCTION

Photovoltaic system is a crucial source of energy, it's characterized by an excellent potential, high reliability, easy to put in, zero fuel costs, very low maintenance costs, and therefore the lack of noise thanks to the absence of moving parts [1]. Thanks to these advantages, the amount of photovoltaic (PV) systems is increasing rapidly everywhere the planet, within the last years. Grid connected PV plants with sizes varying from a couple of kWp (domestic plants) to many MWp (utility-scale plants) represent world-wide the facility technology with the very best rate of growth.

In a PV plant energy production depends on different kinds of factors such as electrical and geometrical configurations, the nominal characteristics of the components of the solar PV system, shading factor due to weather conditions, availability of the plant and location , failures which will occur during its operation, and other non-critical factors [2]. Various factors have been observed to have contributed to losses within a PV plant such as MPPT error, losses in wiring, faults such as short circuit and open circuit faults, ageing of materials and different environmental like operating temperature, irradiation levels and running conditions. [3]. Additionally, other losses are mentioned the faults occurred in PV plant (PV array DC-DC and DC-AC converters). The detection and diagnosis of faults in PV systems are vital for the safe operation of the PV plant [4].

Nowadays, many techniques are developed to detect and diagnosis the faults in PV systems. The methods are often divided into two categories: the primary one doesn't require climate data, and therefore the other is especially supported the analysis of the present and therefore the voltage delivered by the PV array. Other researchers include intelligent based approaches, however, most published methods cannot detect the occurrence of quite fault within the PV array and a few others give only the possible fault types (i.e. they're unable to spot the precise location of fault) [5][6] . During this paper, an intelligent technique for detecting and classification of faults which will appear in PV cells, PV modules, PV strings, and bypass diodes with and without shadow effect has been presented [7].

## II. PROPOSED METHODOLOGY

### A. Block Diagram

Figure 1 shows the block diagram of proposed approach in which solar PV module interconnected system design. Then after designing, different fault conditions were simulated using resistance inserted in circuit. The output voltage, current and power were measured at different and that measures parameters were transferred to excel sheet for generation of training data set. That training data set was utilized for training ANN for classification of different PV system fault condition.

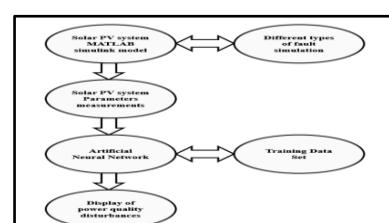


Fig.1. Block diagram of proposed methodology



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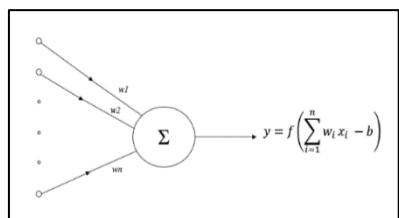
## B. Artificial Neural Network

Roughly speaking, a neural network may be a collection of artificial neurons. A man-made neuron may be a mathematical model of a biological neuron in its simplest form. From our understanding, biological neurons are viewed as elementary units for information science in any *sistema nervosum* [8]. Without claiming its neurobiological validity, the mathematical model of a man-made neuron is predicated on the subsequent theses:

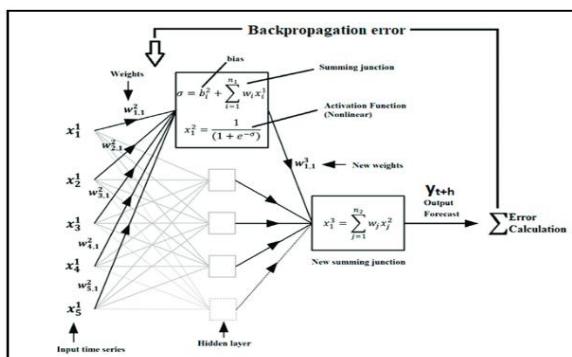
1. Neurons are the elementary units during a *sistema nervosum* at which information science occurs.
2. Incoming information is within the sort of signals that are passed between neurons through connection links.
3. Each connection link features a proper weight that multiplies the signal transmitted.
4. Each neuron has an internal action, depending on a bias or firing threshold, resulting in an activation function being applied to the weighted sum of the input signals to produce an output signal [8]. Thus, when input signals  $x_1, x_2, \dots, x_n$  reach the neuron through connection links with associated weights  $w_1, w_2, \dots, w_n$ , respectively, the resulting input to the neuron, called the net input, is the weighted sum. If the firing threshold is  $b$  and the activation function is  $f$ , then the output of that neuron is

$$y = f \left( \sum_{i=1}^n w_i x_i - b \right)$$

In the first computational model for artificial neurons, proposed by McCulloch and Pitts, outputs are binary, and the function  $f$  is the step function.



**Fig.2. First model for artificial neuron**



**Fig.3. ANN Back propagation algorithm for training**

Defined by

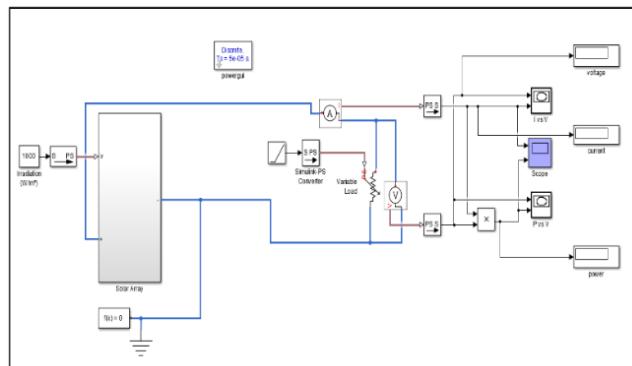
$$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

so that the activation of that neuron is

$$f \left( \sum_{i=1}^n (w_i \cdot x_i - b) \right) = \begin{cases} 1 & \text{if } \sum_{i=1}^n w_i \\ 0 & \text{if } \sum_{i=1}^n w_i \end{cases}$$

This is depicted in Figure 1. An artificial neuron is characterized by the parameters  $\theta = (w_1, w_2, \dots, w_n, b, f)$

## III. SIMULATION MODEL



**Fig.4. MATLAB model for simulating different faults.**

Figure 4 shows the MATLAB simulation model of solar PV array system connected with PV and VI characteristics calibration system. The complete MATLAB simulation model was implemented in MATLAB 2015 software. In this proposed approach, PV array system was design and all fault conditions like module to module fault, module to ground fault, shading effect fault, mismatch faults.

In this approach, different fault condition was simulated in modules and then identifies and analyzed the VI and PV characteristics. In next topic the result of different fault conditions is presented.

**Table I. Matlab Simulation model parameter specifications**

Sr. No	Name of simulation block	Parameters specification
1	Solar cell	Short circuit current $I_{sc} = 6.75$ A; Open circuit voltage $V_{oc} = 2$ V; Irradiation = 1000 w/m <sup>2</sup> ; Quality factor $N = 1.5$ ; Series resistance $R_s = 50$ m Ohm; Energy gap = 1.1 eV; Measurement temperature = 25 C; Device simulation temperature = 25 C
2	Ramp for resistive load variation	Slope = 1; Start time = 0 Sec; Initial output = 0
3	Variable load	Load varied from 1 Ohm to Infinity Ohm depends on time of simulation

## A. PV and VI Characteristics

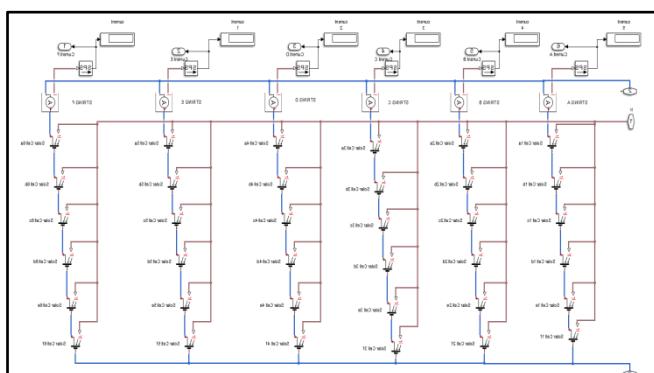
**Table II. Ratings of solar array system at 1000 w/m<sup>2</sup> and 25C STP Condition**

Standard conditions	T=25 C, S=1000 W/m <sup>2</sup>
Output voltage	12 Volts
Normal output current	30 Amp
Output power	360 W

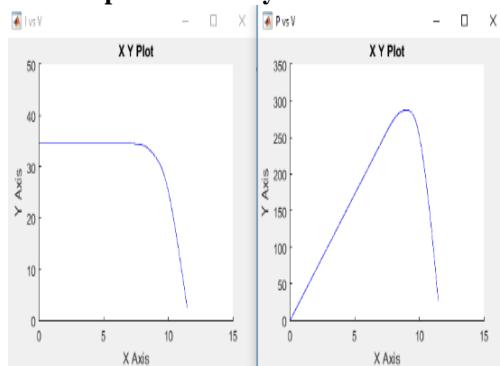
The I-V characteristic describes the behaviors of PV arrays, and it is a basic tool for normal and fault analysis. In a faulted PV array with series-parallel configuration, the normal part and faulted part share the same operation voltage.



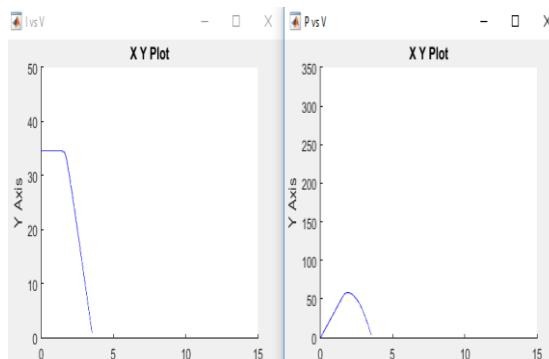
According to the given I-V characteristics for PV arrays and array operation voltage, it is possible to derive the working points of normal and faulted parts of the array. [9]



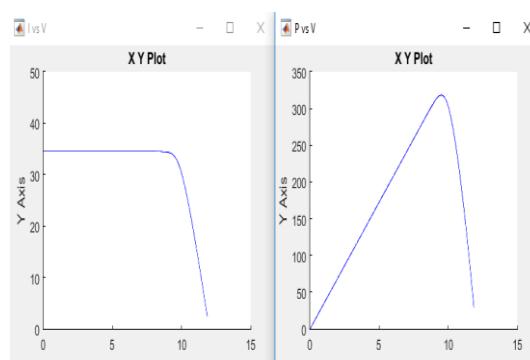
**Fig.5. MATLAB Simulation model of 6 arrays connected photovoltaic system model**



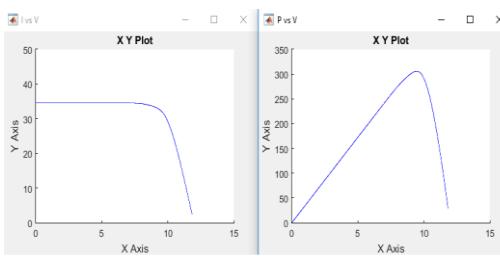
**Fig.6. VI and PV characteristics for module 1f-Gnd fault at 1000 W/m2 irradiation**



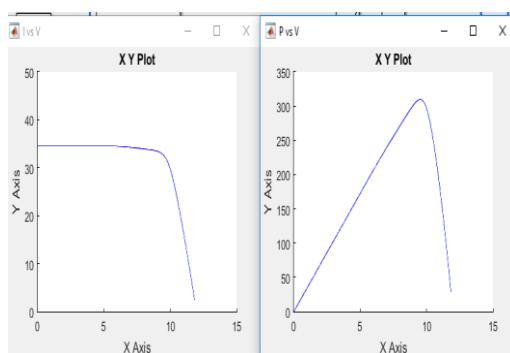
**Fig.7. VI and PV characteristics for module to module fault in cell 5b to cell 5e at 1000 W/m2 irradiation**



**Fig.8. VI and PV characteristics for open circuit fault in string A at 1000 W/m2**

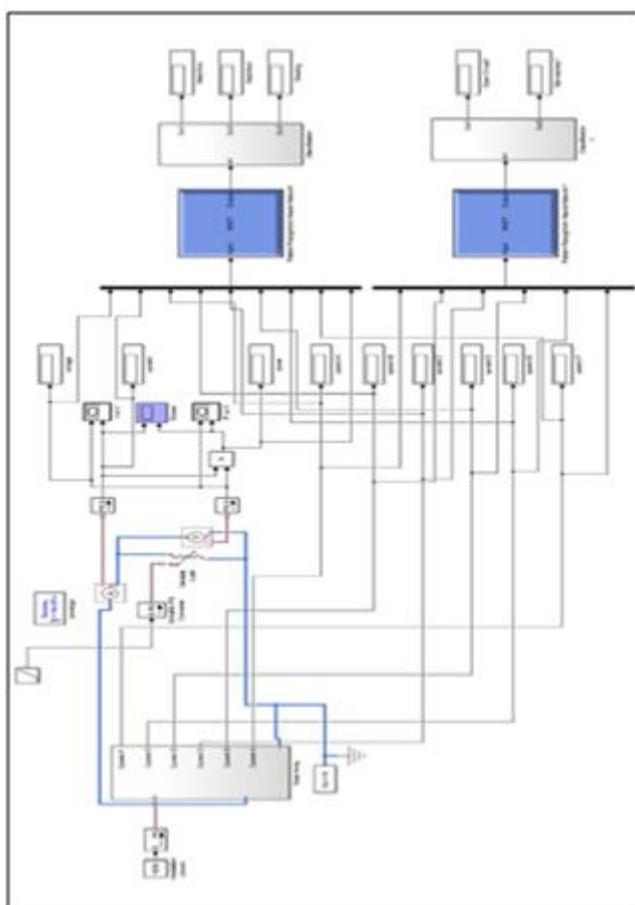


**Fig.9. VI and PV characteristics for mismatch fault between module 1a and 2c at 1000 W/m2 irradiation**



**Fig.10. VI and PV characteristics when shading effect occurs in between 5a and 5b solar modules at 1000 W/m2**

## B. Simulation model for solar PV fault classification



**Fig.11. MATLAB Simulation model for solar PV fault classification using Artificial Neural Network (ANN).**

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**Table III. Training data set for ANN 1 & 2 samples for PV module fault classification .**

Sr No	Condition	Type of fault	Solar irradiation (W/m2)	Voltage	Current	Current A	Current B	Current C	Current D	Current E	Current F	Power
1	Solar Cell1a-GN	Module to ground	1000	3.471	0.69	-28.06	5.75	5.75	5.75	5.75	5.75	2.41
2	Solar Cell 3c-GN	Module to ground	800	9.327	1.865	4.57	4.57	-21.03	4.57	4.57	4.57	17.4
3	Solar Cell 5b-GN	Module to ground	600	11.32	2.26	1.45	-4.98	1.45	1.45	1.45	1.45	25.63
4	Solar Cell 1c-GN	Module to ground	400	2.58	0.51	2.3	2.3	-10.98	2.3	2.3	2.3	1.33
5	Modules 1b-3b	Module to module	1000	11.47	2.294	1.524	-5.327	1.524	1.524	1.524	1.524	26.32
6	Module 2b-3b-4b	Module to module	800	9.355	1.871	4.577	-21.01	4.577	4.577	4.577	4.577	17.5
7	Modules 2c-3c-4c	Module to module	600	8.494	1.699	3.45	3.45	-15.55	3.45	3.45	3.45	14.43
8	Modules 2e-3e-4e	Module to module	400	7.599	1.52	2.3	2.3	2.3	2.3	-9.98	2.3	11.55
9	Modules 2f-3f-4f-5f	Module to module	1000	6.911	1.382	5.75	5.75	5.75	5.75	5.75	-27.37	9.554
10	Modules 1e-2e-3e-4e	Module to module	800	6.322	1.264	4.6	4.6	4.6	4.6	-21.74	4.6	7.995
11	Modules 3f-4f-5f-6f	Module to module	600	5.728	1.146	3.45	3.45	3.45	3.45	3.45	-16.1	6.563
12	Modules 1a-2a-3a-4a	Module to module	400	5.124	1.025	-10.48	2.3	2.3	2.3	2.3	2.3	5.252
13	Solar Cell 2a	Shading fault	1000	11.84	2.369	0.098	0.45	0.45	0.45	0.45	0.45	28.06
14	Solar Cell 6f	Shading fault	800	11.79	2.358	0.45	0.45	0.45	0.45	0.45	0.93	27.79
15	Solar Cell 3f	Shading fault	600	11.71	2.343	0.45	0.45	0.45	0.45	0.45	0.08	27.44
16	Solar Cell 5c	Shading fault	400	11.6	2.32	0.45	0.45	0.02	0.45	0.45	0.45	26.91
17	Modules 5a-6a	Shading fault	1000	11.79	2.357	-0.77	0.62	0.62	0.62	0.62	0.62	27.78
18	Modules 5d-6d	Shading fault	800	11.73	2.345	0.62	0.62	0.62	-0.8	0.62	0.62	27.5
19	Modules 2b-3b	Shading fault	600	11.64	2.328	0.64	-0.89	0.64	0.64	0.64	0.64	27.1
20	Modules 1b-2b	Shading fault	400	11.48	2.296	0.73	-1.354	0.73	0.73	0.73	0.73	26.36
21	Modules 1f-2f-3f	Shading fault	1000	11.69	2.338	0.9	0.9	0.9	0.9	0.9	-2.19	27.32
22	Modules 2d-3d-4d	Shading fault	800	11.62	2.324	0.91	0.91	0.91	-2.26	0.91	0.91	27.01
23	Modules 1f-2f-3f	Shading fault	600	11.52	2.304	0.95	0.95	0.95	0.95	0.95	-2.48	26.54
24	Modules 3c-4c-5c	Shading fault	400	11.32	2.264	1.07	1.07	-3.1	1.07	1.07	1.07	25.63
25	Modules 3b-4b-5b-6b	Shading fault	1000	11.55	2.311	1.29	-4.16	1.29	1.29	1.29	1.29	26.69
26	Modules 1c-2c-3c-4c	Shading fault	800	11.48	2.296	1.3	1.3	-4.23	1.3	1.3	1.3	26.35
27	Modules 3d-4d-5d-6d	Shading fault	600	11.36	2.272	1.34	1.34	1.34	-4.47	1.34	1.34	25.82
28	Modules 3e-4e-5e-6e	Shading fault	400	11.12	2.224	1.45	1.45	1.45	1.45	-5	1.45	24.74

1	Solar string E	Open circuit fault	1000	11.84	2.368	0.4735	0.4735	0.4735	0.4735	0.000162	0.4735	28.03
2	Solar string D	Open circuit fault	800	11.78	2.356	0.4712	0.4712	0.4712	0.000166	0.4712	0.4712	27.76
3	Solar string D	Open circuit fault	600	11.71	2.342	0.4684	0.4684	0.4684	0.000174	0.4684	0.4684	27.41
4	Modules 3d-4e	Mismatch fault	1000	11.83	2.366	0.4858	0.4858	0.4858	-1.032	1.457	0.4858	28.03
5	Modules 3d-4e	Mismatch fault	800	11.78	2.356	0.4871	0.4871	0.4871	-1.026	1.434	0.4871	27.75
6	Modules 2d-3e	Mismatch fault	600	11.7	2.34	0.4921	0.4921	0.4921	-1.481	1.852	0.4921	27.37
7	Modules 2b-3c	Mismatch fault	400	11.58	2.315	0.5117	-1.434	1.703	0.5117	0.5117	0.5117	26.8
8	Modules 2b-3c	Mismatch fault	200	11.28	2.255	0.6012	-1.274	1.124	0.6012	0.6012	0.6012	25.43



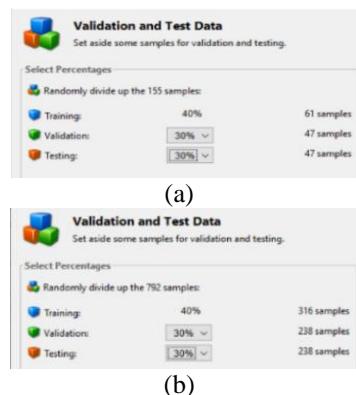
**Table IV. Target output of ANN for solar PV module fault classification.**

Name of fault	Fault case num ber	Module to ground	Module to module	Open circuit fault	Shad- ing effect	Mism- atch fault
Module to ground	1	1	0	0	0	0
Module to module	2	0	1	0	0	0
Shading effect	4	0	0	0	1	0
Open circuit	3	0	0	1	0	0
Mismatch fault	5	0	0	0	0	1

### C. Artificial Neural Network Training

MATLAB software tool is used for neural network training for solar PV system for different types of fault classification which was tested out in this research. Separate neural network structure, the database comprised of various parameters for classification and input for neural network such as solar PV voltage, line current of all solar modules combined and current of each different strings and output power. The output parameters such as output voltage, output current, output current of each string of solar grid and output power were measured at different fault conditions of the solar PV module and that parameters were utilized for training data set for neural network training in MATLAB for the ANN system.

In the ANN MATLAB training the prominent five types of fault conditions like open circuit fault, module to ground, module to module, and shading effect and mismatch faults were tested. All these different types of fault conditions were simulated using MATLAB in the simulink model. Training data set of neural networks is shown in table III and corresponding target output of ANN is shown in table IV.



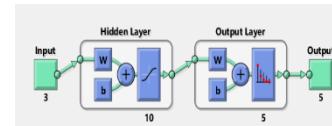
**Fig.12. MATLAB Simulink: Training, Validation and Testing input data set for both ANN1 and ANN2.**

Figure 12. indicates the percentage of training data set, validation data set and testing data set for ANN1 and ANN2 in which 61 (Fig. 12 (a)) and 316 (Fig. 12 (b)) numbers of training samples for both the ANNs selected from entire 155 and 792 samples respectively.

Training data set: These values of data set are presented to the neural network during training, and the network is adjusted according to its error values or in simple terms it is used to adjust the weights on the neural network.

Validation data set: The values in this data set are used to measure network generalization, and to stop the training when generalization results stops improving after required epochs thus used to minimize overfitting.

Testing data set: These values have no overall effect on training and so they only provide an independent measure of the performance of network during and after training in neural network MATLAB toolbox and thus can be used only for testing the final solution in order to confirm the actual predictive power of the network.

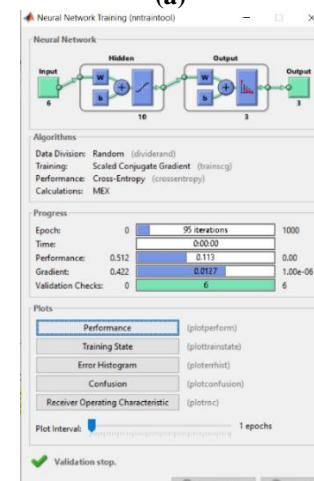


**Fig.13. Hidden Layer and Out Layer count in the MATLAB toolbox.**

## IV. RESULTS



**(a)**



**(b)**

**Fig.14. ANN1 and ANN2 MATLAB training performance windows.**

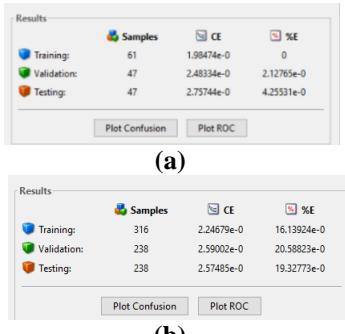
Figure 13. shows the generalized structure of back propagation based Artificial Neural Network in which inputs are solar PV voltage,



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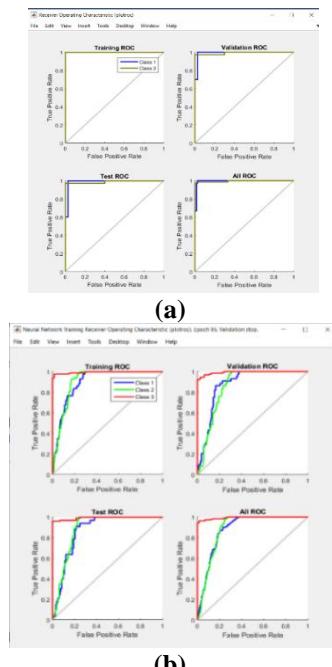
current and power and then corresponding targets are different solar PV module fault as shown in table III and IV respectively. Hidden layer contains total of 10 neurons and the sigmoidal activation function of each neuron while output neuron contains of total 5 neurons which has soft competitive activation function.

Figure 14 shows the training performance windows for training of PV solar system fault classification neural network. In this total 37 (Fig 14 (a)) and 95 (Fig 14 (b)) epochs are required for complete training of ANN using back propagation algorithm. Gradient for this training was measures as  $1 \times 10^{-6}$ .



**Fig.15. ANN1 and ANN2 percentage error count during training of samples in the training, testing and validation phase.**

Figure 15. shows, for training of ANN, total 61 (Fig 15(a)) and 316 (Fig 15(b)) data samples were utilized out of which 155 and 792 data set values respectively i.e. almost 70% data utilized for training. For validation and testing almost 30% dataset was utilized. Also, MSE (Mean square error) for all data set was 0 % and 16.13 % respectively after successful training of ANN.

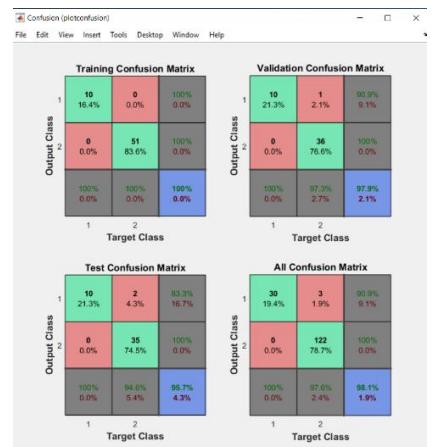


**Fig.16. ROC (Receiver operating characteristics) for training of ANN1 and ANN2.**

Figure 16. The receiver operating characteristic (ROC) may be a metric to check the standard of classifiers. For every class of a classifier, roc applies threshold values across the interval [0,1] to outputs.[10] For every threshold, two values are calculated, truth Positive Ratio (the number

of outputs greater or adequate to the edge, divided by the amount of 1 targets), and therefore the False Positive Ratio (the number of outputs but the edge, divided by the amount of zero targets).

Figure 17 (b) shows that no False positives were classified and all the data is perfectly classified for the three types of PV solar system fault cases and shows that 83.9 % data is perfectly classified and 16.1% data is not classified properly i.e. ANN confused for classification. It means that for remaining 16.1% data set neural network was in confusion state for classify the fault. Whereas for Figure 17 (a) also shows that no False positives were classified and all the data is perfectly classified for the two types of PV solar system fault cases and shows that 97.9 % data is perfectly classified and 2.1% data did not classify properly.



(a)



**Fig.17. Training confusion matrix for both ANNs.**

**Table V. Final Result Conclusion**

	Epochs	% Training Error	Classified Cases	False Positives
ANN1	37/1000	0	100%	0
ANN2	95/1000	16.13	83.9%	0

## V. CONCLUSION

In thesis given proposed approach, different types of fault conditions which are generally seen in photovoltaic system are simulated during which if any circuit fault occurs then output current an output voltage decreases very rapidly as compared with module to module or module to ground fault.

The simulation model takes the solar irradiance level and PV module temperature as inputs and predict accurate steady-state performance compared with the manufacturer's datasheet. The used model is also flexible and diverse enough to simulate solar PV arrays with different values of input, with or without bypass diodes and diverse technologies.

MATLAB based neural network using Back-propagation algorithm was used for classification of different types of solar PV faults that were simulated. ANN1 box classified for the three types of PV solar system fault cases and shows that 83.9 % data is perfectly classified and 16.1% data is not classified also all the data is perfectly classified for ANN2 box the other two types of PV solar system fault cases and shows that 97.9 % data is perfectly classified and 2.1% data did not classify properly. Thus it can be concluded that by using ANN tool we can reduce the error rate and increase the accuracy of fault detection in the photovoltaic system.

Unlike previous works in the literatures, this PV simulation model is modular, versatile and scalable to build PV arrays with various configurations, which is especially useful for studies of different types of fault scenarios as well as PV modules interconnection for increasing the efficiency of the system.

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