ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

Back Propagation Algorithm Based Approach to Recognize and Categorize the DC Fault in PV Module

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Abstract: In the present era, the role of solar photovoltaic (PV) in the distributed generation has become inevitable and it is also the need of the hour. In addition to distributed generations (DGs) in the utility grid demand for decent power quality, secure operation and islanding protection of the grid interconnection. In order to maintain the quality of the power, one need to accelerate the procedure of finding the fault, reduce the downtime and bring the system back to normal condition. Many diagnostic approaches were proposed in the past to identify the PV faults but they are old school methods and sometimes become unmanageable particularly in case of multiple faults and critical PV system. In this paper recognition and categorization of all possible DC faults of a grid-connected PV system using an artificial neural network (ANN), an artificial intelligence technique is presented. The simulation of ANN was done over 100 kW solar PV system connected to an 11 kV grid. Five inputs were fed to the ANN namely, PV voltage (Vpv), current (Ipv) and power (P) (PV array parameters) and irradiance (G) and module temperature (T) (environmental data). Also, there were 5 output nodes as a DC fault indicators namely, Short-Circuit; Open-Circuit, Degradation, Shading and Charging Module. The optimized neural network architecture comprised of 5 neurons in the input layer, 20 neurons in the hidden layer and 5 neurons in the output layer. The hyperbolic tangent sigmoid transfer function was used as an activation function for the hidden as well as output layers. The ANN network was trained with over 1000 samples using back propagation algorithm with the accuracy of 0.01. To achieve the set error goal of 0.01 the ANN performance converges within the 1000 epochs. The neural network was tested for additional 1040 samples which were not included in the training data. The results of the tested data were obtained with the accuracy of 99%. It is found that the proposed system has proved its goodness with the accuracy of 99% for the practical applications when compared with the other artificial intelligence techniques like fuzzy system, expert knowledge, etc.

Index Terms: Artificial Neural Network (ANN), DC side Faults, Grid connected PV system.

I. INTRODUCTION

Power outage issue is the utmost concerning issue in the recent past. If renewable resources are used as power sources, they not only resolve the problem but also make energy more sustainable. When talking about sustainable power, photovoltaic (PV) framework has an important role to play. They are favored because of their clean and eco-friendly nature. Developments are continuously being carried out to make solar panels more efficient [1]. Efficiency is defined as the ratio of maximum attainable output power to the incident sun energy. The panel module is the key part of any PV system. The output of the panel varies with the level of solar irradiance and temperature. This drives to use a charger module that controls the output PV panel and feeds the power to the load. The competence of the PV panels is affected by their faults and hence, flawless operation of the PV cells becomes a very important task. Faults in the PV panel causes two problems: (1) It leads to a reverse bias operation which result in hot spots and cause more faulty cells in that cell group, (2) it limits the output current of the panel [2]. Presently, numerous identification techniques are established for faults recognition in PV systems. One of them is the earth capacitance measurement method (ECM) which does not require any climate data [3] but has an electrical method for locating the connectivity issues of PV module in a string. The time-domain reflectometry (TDR) method another technique to detect fault, measures electrical characteristic of a transmission line, which can recognize not only the connectivity issues in the string but also impedance alteration due to degradation [4]. Some other methods are there based on statistical analysis in which high level of accuracy along with high speed of fault diagnosis was achieved using variance test (ANOVA) and non-parametric Kruskale-Wallis test [5]. Alternative method is remote monitoring and fault recognition method of small grid connected photovoltaic (GCPV) systems which is presented in [6] where climate data were observed from satellites that is used to substitute on-site measurements. Different researchers utilized atmospheric information measured by local sensors on the plants. Chao et. al proposed modeling and fault diagnosis based on the extended correlation function and the matter element model [7]. However, their proposed method doesn't determine that much accuracy for different type of faults. Chouder and Silvestre proposed automatic supervision and fault detection of PV system using power losses analysis to generate a faulty signal [8]. In this method, the dc current and voltage ratio are defined as the indicators of the fault types. However, their approach is only giving the possible fault types only. Yue Wu et al., [9] proposed novel intelligent fault diagnosis method based on the improved simulated annealing radial basis function (SA-RBF) extreme learning machine to detect the fault in photovoltaic array. However, there accuracy to detect the faults was not up to that mark. In fact, the study about fault recognition and diagnosis requires very accurate detection results. Otherwise, the information might misinform the operator. Based on these preceding studies, there are still possible ways to improve the recognition and categorization methods. Since the accuracy, fast computation and ease are the significant issue in this kind of study, intelligent technique like artificial neural network (ANN) can be a prominent solution. However, there has been less work done over ANN to resolve the above problem. In this paper, the artificial neural network (ANN) is utilized to categorize and recognize every single conceivable DC fault in 100 kW GCPV system connected to a 11 kV grid.

II. FAULT CATEGORIZATION IN GRID CONNECTED PV SYSTEM

PV Faults can be divided in two parts of the system: DC side and AC side. The classification of faults is shown in Fig. 1. In this paper we are considering only DC side faults.

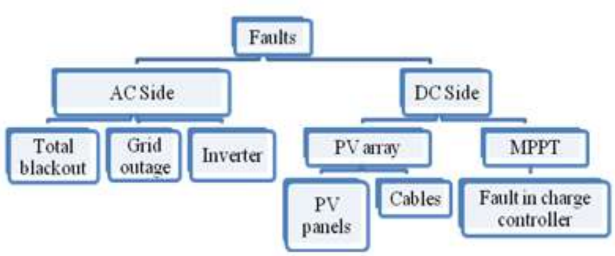

Fig.1. Fault Classification associated with solar PV.

A. DC side faults

The faults arise in DC side of the GCPV system is classified into two main types: (1) PV Array Faults and (2) Maximum Power Point Tracking (MPPT) fault.

Further, PV array faults can be classified into two core groups, PV panel fault and cable fault. Fig. 2 shows different types of faults in PV Panel/Module.

1.1 PV panel Faults

1.1.1 Earth fault

This fault occurs when the circuit builds up an inadvertent way to ground. Two kinds of grounding are associated for PV system that is: system grounding and hardware grounding. In system grounding the negative conductor is grounded through the earth fault protection device (GEFPD) in the PV inverter while in hardware grounding the uncovered non-current-conveying metallic parts of PV module is grounded [10].

1.1.2 Bridging fault

Bridging fault occurs when there is a low-resistance linking between two points at different potential energy in string of module or cable of PV panel. It is basically the failure in an insulation of cables that are caused due to creature biting the cable insulation, mechanical harm and water entrance or corrosion.

1.1.3 Open Circuit Fault

An open circuit fault occurs when one of the current-carrying paths in series with the load is wrecked or opened. The deprived networks between cells, plugging and unplugging connectors at junction boxes, or breaks in wires cause these fault.

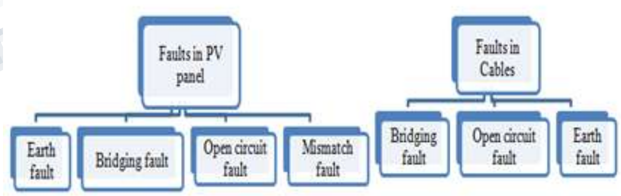

Fig. 2. Fault categorization associated with PV array.

1.1.4 Mismatch Fault

Mismatches in PV modules occur when the electrical parameters of one cell or a group of cells is different from the other group of cells. These faults result in irreversible harm on PV modules and thereby huge power loss occurs. These deficiencies can be divided into temporary and fixed losses. Temporary losses happens when a part of the panels array are shaded by shade of the building itself, light posts, smokestacks, trees, mists, soil, snow and other light-blocking deterrents [11]. Fixed losses are the faults in hotspot, soldering and degradation of leads. Hotspot warming happens when the operating current surpasses the diminished current of a shadowed or defective cell or

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

group of cells inside the module [12]. Soldering issue can be recognized in resistive solder bond amongst cell and contacted ribbons.

1.2 Cable Faults

Cable fault occurs due to the immature connection at the back side of a solar panel or in the corner and curved area of cable [13]. These faults are caused due to human intervention at the time of installation which results in voltage and power sag.

1.3. MPPT Faults

MPPT faults occur when the charge regulators fail which results in reduced output voltage and power.

Table I. Measured data from solar panel

Time (a.m/p.m)	Voltage (V)	Currents (A)	Power (Watts)	Solar irradiance (Watt/m^2)	Module Temperature (^{0}C)
9:30 a.m	10.97	2.80	30.72	276	39.40^0
10:30 a.m	11.01	2.95	38.72	340	40.40^0
11.30 a.m	13.85	6.6	91.47	465	43.10^0
12:30 p.m	18.71	7.6	142.2	764	48.68^0
1:00 p.m	22.83	8.1	185	997	57.50^0
1:30 p.m	20.83	7.1	180	985	54.50^0
9:30 a.m	10.87	2.89	34.72	283	40.40^0
10:30 a.m	11.21	2.99	39.72	348	41.40^0
11:30 a.m	12.6	4.5	56.72	276	44.20
12:30 p.m	1971	7.9	162.2	802	50.68^0
1:00 p.m	22.93	8.5	196	992	55.50^0
1:30 p.m	20.43	6.9	175	979	52.50^0

III. MODELING OF ARTIFICIAL NEURAL NETWORK

Nervous system in a human brain is stimulated by the neural network (NN). Artificial neural network (ANN) can be characterized as parallel dispersed processor consisting of modest processing units. High precision of validation with fast computational speed is the property by which ANN algorithm is recognized [14]. Numerous fields where ANNs can be applied successfully like data analysis, fault diagnosis, voice and image recognition, process monitoring, automatic control, optimization resolution, etc. [15]. Usually, the ANN methods have three vital stages. They are: data collection, data training (or learning) process and validation of its output. ANN utilizes distinctive training algorithms like back propagation (BP), Levenberg Marquardt (LM), radial basis function (RBF). Among these BP algorithm is superior to other algorithms due to its lesser union time and higher precision [16]. There are three main layers in ANN architecture: input, output and hidden layers. The proposed system is a general purpose PV system. In this paper recognition and categorization of all possible DC faults of a grid connected PV system using ANN, an artificial intelligence technique is presented. The simulation of ANN was done over 100 kW solar PV system connected to a 11 kV grid. In this experiment, PV current, voltage, module temperature, solar irradiance and power in normal sunny days have been measured as shown in Table I.

Five inputs were fed to the ANN namely, PV voltage (Vpv), current (Ipv) and power (P) (PV array parameters) and irradiance (G) and module temperature (T) (environmental data).

Also, there were 5 output nodes as a DC fault indicators namely, Short-Circuit; Open-Circuit, Degradation, Shading and Charging Module. The optimized neural network architecture comprised of 5 neurons in the input layer, 20 neurons in the hidden layer and 5 neurons in the output layer. The model of ANN is trained with this architecture and then the characteristics of the ANN model are evaluated. The network gets the outside info, scales it by weights and predispositions and passes it to the neurons in the following layer. Each layer having neuron gets its contribution from the previous layer. The hyperbolic tangent sigmoid transfer function was used as an activation function for the hidden as well as output layers. From table 1 we have taken two data for environment testing conditions; module temperature and irradiance value as 39.400, 48.680 and 276, 764 Watt/m2 respectively for simulation are results are shown in Table II. Likewise, there were around 1295 samples were tested for module temperature and irradiance parameters. Similarly, different results were also simulated for different module temperature and irradiance values.

IV. RESULTS AND DISCUSSION

All the DC faults in GCPV system are simulated over 100 kW solar PV system connected to a 11 kV grid, and the measured data has been fed to ANN using MATLAB Simulink model. The greatest option comprises of 5 neurons in the input layer, 20 in the hidden layer and 5 neurons in the output layer as illustrated in Fig. 3. The

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 4, April 2018

accompanying parameters are placed to train the ANN model:

Training pattern = 1295 samples
Learning rate = 0.001
Error set objective = 0.01
Number of epochs = 1000
Momentum = 0.95

In training phase, the 10% cross-validation method used to solve over the fitting problem. For training the network, 75% of samples was utilized, 10% used to validate the network and 15% used for test process. To fairly judge the performance of the systems, four different factual markers were utilized. These markers are mean absolute error (MAE), mean squared error (MSE), coefficient of determination (R2) and mean absolute percentage error (MAPE) [18]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_{predicted} - Y_{true}| \qquad (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (Y_{predicted} - Y_{true})^2 \qquad (2)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{Y_{predicted} - Y_{true}}{Y_{true}} \right|^2 \qquad (3)$$

Where $Y_{predicted}$ and Y_{true} are estimated and measured fault values over panels by the models, respectively. From the factual measures stated above, MAPE is the vital measurable quantity in that it mentions utilization of every single objective reality and has the smallest fluctuation from sample to sample.

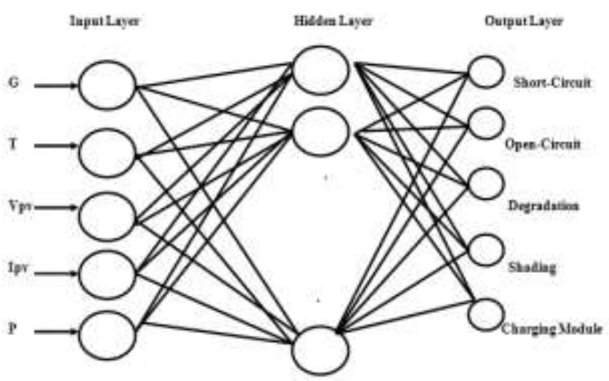

Fig. 3. Projected architecture of ANN.

Variety of users easily understands MAPE, so it is frequently utilized for reporting. However, MSE will also be used for performance analysis, based on this the optimal number of neurons in hidden layer will be decided. Mean square error (execution goal = 9.99 × 10-3) is achieved which is lower than the set objective in 1000 epochs as shown in Fig. 4. The validation showed the accuracy of trained ANN model that trained the whole network with the data which were fed in the starting of training and the mean square error observed for the validation was 8.4968 × 10-3 which was less than the set error objective. Table II represents the simulated results obtained from the proposed artificial neural network system which has been compared with the other artificial intelligence techniques [9, 17]. It is found that, the proposed system has demonstrated its noteworthy performance. However, the proposed system can be used for finding numerous sorts of real-time PV systems in decent way. Thus, the performance of these systems can be amended. ANN model was tested with the other data having 1040 samples which were not included in the training set to ensure that the prediction of dust by the ANN is fulfilled or not. Tested network using whole dataset and results are depicted in Figure 5. Network test error obtained as 1.02023e-3 and regression coefficient (R) obtained as 9.9512e – 1. The mean absolute percentage error (MAPE) of the ANN model is under 0.1% and in this way taking into report the accuracy in the estimation of solar irradiance, module temperature, PV module current, voltage, and misfortunes in association wires, which is roughly 0.1%, consequently, the overall error is around 0.2%. Figure 6 shows confusion matrix which tells that the ANN has successfully recognized and categorized the different types of fault which supports the overall error of 0.2%.

Table II.Simulated results obtained from an ANN

Environment Conditions			Simulation Results			
Type of faults	Temperature (°C)	Irradiation (W/m²)	ANN (Proposed System)		Artificial Intelligence Techniques [9,17]	
			Accuracy (%)	Time (sec.)	Accuracy (%)	Time (sec.)
Short-Circuit	39.40	276	99.1	6.1	90.1	10.5
	48.68	764	100	6.2	95	9.6
Open-Circuit	39.40	276	99.5	5.8	89.7	15.8
	48.68	764	100	5.9	95	7.9
Degradation	39.40	276	99.6	5.5	92.3	10.7
	48.68	764	100	5.3	96	12.8
Shading	39.40	276	99.5	6.4	93.5	9.7
	48.68	764	99.4	5.9	93.4	9.9
Charging	39.40	276	99	6.7	92.6	11.3

Module	48.68	764	99.4	5.9	97.8	10.6

CONCLUSION

The recognition, categorization and simulation of all possible DC faults in GCPV system have been presented. Recognition and categorization of faults with trouble free ANN model has been developed for 100 kW solar PV system connected to a 11 kV grid. There were 5 inputs that were trained and tested, accordingly five outputs were also trained and tested for different data which were not mentioned in the previous training data. With the help of confusion matrix it was able to classify and detect the faults on the PV panel. From the results presented, it can be concluded that ANN has capability to effectively detect and classify the fault data with an accuracy of 99%. The approval too includes investigation of the adequacy of the trained data when copying with obscure information, i.e., data which are not included in the training. This proves the system has high robustness when compared to other techniques.

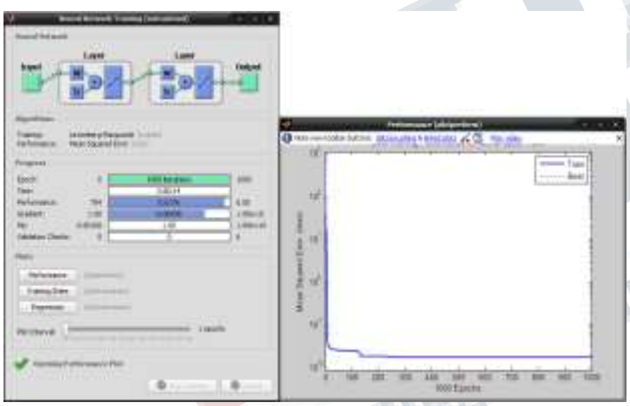

Fig. 4. Training results of ANN in Matlab Simulink and evolution of the performance error

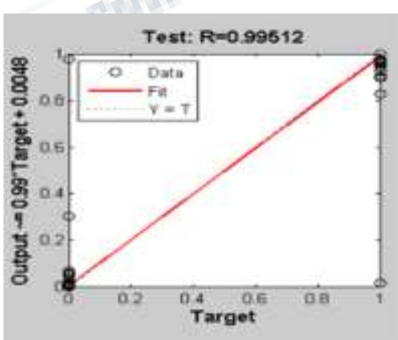

Fig. 5. Test phase performance of ANN model.

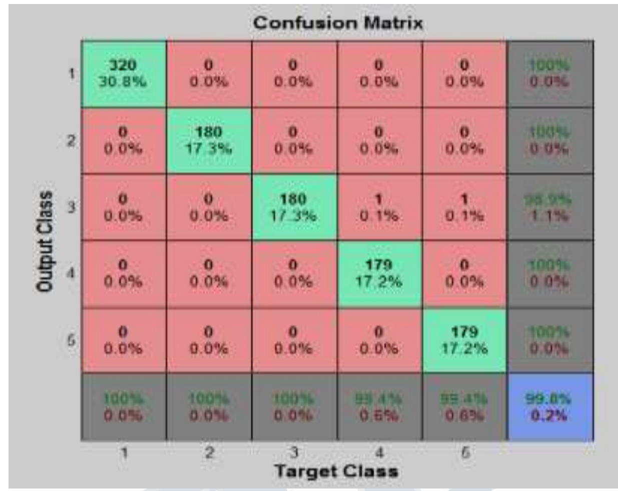

Fig. 6. Confusion matrix (detecting and classifying different faults: 1- Short-Circuit, 2- Open-Circuit, 3- Degradation, 4- Shading and 5- Charging Module).

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