Fault identification in a grid connected solar PV system using Back propagation Neural Network

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Abstract. Albeit the government buoy up the penetration of renewable energy sources (RES) particularly solar photovoltaic (PV) system, the dependency on fossil fuels is still growing. The power generation using solar PV system may enhance when the enactment of solar PV system is improved. The faults occurred in the system is an important performance degradation factor. Incessant studies have been performed to identify and mitigate the faults. Currently, several smart techniques are utilized to identify the faults rapidly. In this study, Back Propagation Neural Network (BPNN) has been implemented to identify the faults. The output power get degraded when the faults happened in source side, Maximum Power Point Tracking (MPPT), DC-DC converter, rectifier and grid. The investigations has performed on 100 kW solar PV system using Matlab. The outcomes imply that the proposed method has detected the faults quickly, economically and effectively.

Keywords: Back propagation algorithm, fault identification, AC-GCPV system, Matlab

1 Introduction

The harmful effects of pollutant emitted from conventional power plants increases day by day. So, the penetration of RES in power generation is getting more attention worldwide [1]. All the countries around the world have fixed a renewable energy target and continuously increasing the RES penetration in power generation to achieve them. Photovoltaic (PV) system based electricity production plays a vital in achieving this target [2]. Recently, it is reported that the huge penetration of RES, significantly minimizes the pollutant emission [3]. However, it may cause certain problems for instance protecting equipment organization concerns, accidental islanding and power slaps. So as to attain the valued power it is essential to recognize and resolve the fault happening quickly. In this context, previously, modeling studies have been presented to diagnosis the faults occurring in the PV systems [4-7]. Most of them didn’t utilize standard software and only focused in determinates occurrences such as shadowing or rectifier fault [6], maximum power point (MPP) progress [4,5].
or PV panel faults in divisions of the PV panel [7]. Also, they didn’t juxtaposed with practical data practically noted from real-time PV systems [7,4]. So, a fault identification procedure for 100 kW grid-connected photovoltaic (GCPV) plants is offered [8]. The grouping, recognition and islanding of all probable faults in DCGCPV system have been provided [9], in which 48 W, 24 V panel linked to a 500 W, 58 V grid through a DC-DC converter.

The efficient intelligent techniques for instance neural network (NN) and fuzzy logic systems, had been designed to approximate nonlinear systems without complex mathematical models [10-12]. Amongst the techniques, the Wavelet Fuzzy Neural Network (WFNN) is the combined version of wavelet theory with fuzzy logic and neural network, particularly the wavelet transform has the capability to investigate motion indications to determine the resident data [13-16]. Probabilistic Fuzzy Neural Network (PFNN) is the neural network application of Parzen non-parametric probability density function approximation and Bayes grouping rule. So, PFNN can solve the chance qualms of the input [17-20]. In this paper, with the assist of previous experiences [8,9], different types of failures at source side, MPPT, DC-DC converter, rectifier and grid have been physically generated on 100 kW AC-GCPV system. Several outcomes have been taken from dissimilar kinds of failures which have been fixed as training data. The investigations have been performed using BPNN in Matlab.

2 Grid connected PV (GCPV) system

The GCPV systems are usually tied to the main power utility. The PV system supplies the power to the grid during daytime and withdraw the power from grid during nighttime and cloudy days. PV panels, rectifiers, meters and switches are the chief apparatuses of GCPV system.

- PV Arrays: It is a blend of certain unified solar modules. It converts sunlight directly into DC current.
- Rectifier: It convert the produced DC current into the AC current for applicants.
- Metering: Metering apparatus are employed to specify the enactment of the systems.
- Switches: They are employed for swapping between source side and the grid liable on the characteristics of the source side.

2.1 Factors affecting the output of PV system

The output of PV system depending on the incident sunlight intensity. But, the sunlight is variant in nature. The most important factors that affecting the output of PV system are typical circumstances, dust, temperature, disparity and cabling losses and DC-AC conversion losses [21].

- Typical test condition: The PV system provides rated output only if the system is operated under irradiance of 1000 W/m², solar cell temperature of 25° C, solar
range as sifted by fleeting through 1.5 thickness of ether. PV system is operated under non-standard test conditions, so 5% of losses are allowable.

- Dust: Dust present on the panel exterior block the incident sunlight. Approximately 7% of losses is caused by these dirt and dust.
- Temperature: The output power reduces when there is an increment in the temperature. 11% of loss in power production is caused by temperature effects.
- Disparity and cabling losses: In practical, the extreme power of a PV panel is not same as the amount of the extreme outputs of PV panels arranged. Some differences in module performances result with this loss and it is termed as module mismatch. Approximately, 2% of power losses is caused by this module mismatch.
- DC-AC conversion losses: Losses due to the faults occurring in rectifier wiring and other system parts are responsible for this rectification losses of 10% of the generated power.

These factors are considered to create manual fault in 100 kW GCPV system used in this research. The GCPV model encloses:

1. PV array generating an extreme of 100 kW of power at 1000 W/m² solar irradiance.
2. 5-kHz DC-DC converter elevating voltage from available PV voltage. The P&O based MPPT controller is employed.
3. 1980-Hz (33×60) 3-level 3-phase rectifier. It changes 500 V DC to 260 V AC and maintains standard power factor.
4. 10-kvar capacitor bank is used to eliminate the harmonics that is created by rectifier.
5. 100-kVA 260V/25kV 3 phase coupling transformer.
6. AC grid (25-kV feeder and 120 kV equal transmission system).
7. The array having 66 strings of 5 series-tied modules coupled in equivalent (66×5×305.2 W= 100.7 kW). The provisions of a single module are:
   - No. of series-tied cells: 66.
   - Open-circuit voltage: \(V_{oc}= 64.2 \) V.
   - Short-circuit current: \(I_{sc}= 5.96 \) A.
   - Voltage and current at maximum power: \(V_{mp}=54.7\) V, \(I_{mp}=5.58\) A.

3 Depiction about Artificial Neural Network (ANN)

ANN can able to elucidate the non-linear problems simply, so it can be smeared to fault identification and grouping problems. Also, it can handle massive data effectively. The performance of the ANN is depends on the selection of network type, network architecture (i.e. no. of layers, no. of neurons in every layer, activation functions, parameters of the learning algorithms etc.), expiry conditions etc. The several strictures such as number of active strings, DC-DC converter voltage, ON/OFF status of MPPT, rectifier voltage, PV output power and grid voltage are needed for exact fault identification and organization. These values are noted with several combination of failures. ANN has been operated using these five responses, i.e. employed as the training data. ANN results with the category of the failure.
3.1. Description on BPNN

In BPNN the outcome is reaction into the input layer to evaluate the alteration in the weights values. In two layers ANN, same inputs lead to same output. In order to eliminate this the back propagation algorithm is adopted. The error in each iteration is estimated by instigating from the final stage and by directing the estimated fault rearward. The weights of the back-error-propagation algorithm for NN are selected arbitrarily and send back in an input to get the outcome. After every stage, the weights are restructured and the procedure is repetitive for all the inputs-outputs mixtures given in the training data. This procedure is continued till the converged values for the input values of the goals for a prefixed value of fault lenience. The concept of BPNN is illustrated in Figure 1. This whole procedure is performed by every in the network in retrograde direction [22]. It employs the Mean Square Error (MSE) method for estimating the fault in every repetition.

![Perception of BPNN](image)

**Fig. 1. Perception of BPNN**

BPNN algorithm is given as:

Forward propagation

\[ a_j = \sum_{i}^{m} w_{ji} x_i \]  
(1)

\[ z_j = f(a_j) \]  
(2)

\[ y_j = \sum_{j}^{m} w_{j} z_j \]  
(3)

Output difference

\[ \delta_k = y_k - t_k \]  
(4)

Back propagation for hidden layers

\[ \delta_j = (1 - z_j^2) \sum_{i=1}^{K} w_{ij} \delta_k \]  
(5)

The error regarding weights of first and second layers are estimated. Here the weights are modernized.
where
\( a_j \)  
biased quantity of inputs
\( w_{ji} \)  
weight related with the association
\( x_i \)  
inputs
\( z_i \)  
initiation unit of input that leads an association to unit j
\( \delta_k \)  
derived error at k-th neuron
\( y_i \)  
i-th output
\( y_k \)  
instigated output of unit k
\( t_k \)  
equivalent goal of input
\( \delta_j \)  
derived error with respect to \( a_j \)

The MSE for every output in all iteration is evaluated by

\[
MSE = \frac{1}{N} \sum \left( E_i - E_o \right)^2
\]

where N is no. of iterations, \( E_i \) is expected output and \( E_o \) is out from the prototype.

The learning rate can be improved in every stage by considering the optimal weights [23]. The numbers of iterations taken for convergence, error and execution time are depending on the following factors:

- The structure of NN.
- The no. of layers in NN.
- The intricacy of the considered problem.
- The adopted learning technique.
- The dimension of the input and output data set.

The efficacy of the established ANN is determined by the above factors and the given training data.

4 Results and discussion

The 100 kW PV model used in this study is developed using Matlab and it is illustrated in Figure 2.
The training data is given into ANN after creating five different faults at source side, DC-DC converter, MPPT, rectifier and grid. Initially, the training data set is given as input to ANN for training purposes. It is processed by calculating the ramp and apprising the weights till the error get converged. This data set is called as the authenticating data set and the error is monitored during entire training process. The validation errors increase if the network initiates to fit the given data. And if the number of validation process fails the training procedure is terminated to evade more over appropriate and the network is reverted with least authentication errors. The next process dealt with testing set so as to define the overall enactment of the modeled trained network. The test data set touches minimum MSE at any iteration. The consecutive suckling of input and output pair has been done for training the ANN at different stages. In order to get vast training data for efficient performance different combinations of faults with five major faults conditions has been simulated on 100 kW GCPC system.

4.1. Fault identification

The ANN is operated with five inputs for fault identification process. The different combination of failure and no failure situation are deliberated in modeling the training data set. It is generated with a set of 5 inputs and 5 output. The result might be YES or NO, i.e. 1 or 0, that denotes whether the failure is happened or not. The goal yield for no failure condition would be [0 0 0 0 0]. If a fault happens in grid means the output would be [0 0 0 0 1]. The modeled architecture of ANN has four layers. And it has two hidden layers. The linear transfer functions are used for layer 2 and 3. The results indicate that the training enactment of ANN is good. The overall MSE of the trained network is lower than the pre-fixed value of 0.0001. The MSE value is 0.03709 at the termination of the training of the network. So, this design is selected as final for assumed input and output.

| Results | Location of fault                        |
|---------|-----------------------------------------|
| 0 0 0 0 0 | No fault                               |
| 1 0 0 0 0 | String                                 |
| 0 1 0 0 0 | MPPT                                   |
| 0 0 1 0 0 | DC-DC converter                        |
| 0 0 0 1 0 | Rectifier                              |
| 0 0 0 0 1 | Grid                                   |
| 0 1 0 1 0 | MPPT and rectifier fault               |
| 1 0 0 0 1 | String and grid fault                  |

After confirming that the fault has happened in the system, the ANN tends to categorize the faults. By following the same procedure processed in fault identification, the fault classification procedure has been implemented. So, the ANN
can identify and categorize the faults automatically from the training data. Table 1 shows the model data of the ANN based fault diagnosis or fault classifier system.

5 Conclusion

The benefits of solar PV systems inspire its huge integration into the grid. However, the failures may happen during installation and operation. So, fault analysis becomes a vital role to enhance consistency and efficacy of the system. Conventionally circuit breakers were employed to clear failures and separate them, where the circuits have huge faulty currents. But, in PV system, with the longer reaction time to trigger the breaker device, it is not possible to clear the fault. Because, the PV system has the non-linear current-voltage (I-V) characteristics and the current-limiting nature. Moreover, dissimilar complex failures may happen in the system owing to the erratic ecological situations, numerous fault sites, incongruities amid modules. Consequently, a smart technique is essential. In this paper, the application of BPNN is projected to identify and classify the faults may occur in 100 kW grid tied PV system. The proposed method utilizes the number of active strings, DC-DC converter voltage, ON/OFF condition of MPPT, rectifier voltage, PV output power and grid voltage as inputs to the ANN. The outcomes evident that the enactment of the proposed method is excellent and it is practically implementable.

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