Deep Learning Based Faults Diagnosis in Grid-Connected Photovoltaic Systems

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Abstract. As a renewable energy source, the establishment of photovoltaic (PV) system has essentially expanded. In any case, due to the maturing impacts and external conditions, during operation, PV systems can incur failures. These failures may affect many system components, including converters, PV modules, and connecting lines, which could decrease system effectiveness and performance or even cause the system breakdown. Thus, the fault detection and diagnosis (FDD) is an important aspect in high-efficiency grid-connected PV systems. Deep learning (DL) is used in the most well-known data-driven methodologies. The main benefit of DL algorithms for diagnosis is that they create a high-order, non-linear, and adaptive effort to memorize high-level highlights from PV data, the fault is then classified. Therefore, a comparison of FDD-based DL approaches is presented in this article. These methods include Long-Short Term Memory (LTM), Convolutional Neural Networks (CNN), and Neural Networks (NN). The implementation of the DL techniques-based fault diagnosis is done using an emulated Grid-Connected PV (GCPV) system.
To evaluate the effectiveness of the proposed approaches, we utilize data obtained from a healthy case, which are then injected with several fault scenarios in the DC side and AC side: one fault in the PV sensor, two faults in the PV array level, this is about the DC side and in the other side there are the three-phase inverter fault and the grid external connection fault.
The proposed techniques achieved accuracy from 61.24% to 95.51%, and the models' performance is evaluated.

Keywords: Grid Connected Photovoltaic System (GCPV), Fault Detection and diagnosis (FDD), Deep Learning (DL).

1 Introduction

The majority of energy sources being used today are traditional types like fuels and uranium. These sources are limited in nature and quantity. Additionally, they are continuously diminishing as global energy consumption increases as a result of population growth and industrial expansion. Additionally, it is believed that the main causes of climate change and global warming are fuels like coal, oil, and gas. In order to meet the world's energy needs and reduce the dangerous gases that are released from manufacturing facilities and cars that run on refined fossil fuels, the worldwide is turning to clean and renewable energy sources.

Renewable energy sources including hydro, wind, and solar energy are hopeful contenders to take the place of conventional sources in the coming generations. The International Energy Agency (IEA) claims that wind and solar photovoltaic systems have been the primary drivers of the growth in electricity generation from energy sustainability (PV). With the fast-global expansion and installation of PV systems, fault diagnosis in photovoltaic (PV) systems is becoming continuously more essential with a view to ensure efficient energy collecting, elevated dependability, and little supports costs [1]. Generally speaking, PV systems handle in challenging external requirements, which causes a number of failures in the various PV elements (PV subjects, circuit, power electronics interface, etc.). To overcome these difficulties, it is crucial to develop effective and extensive fault diagnosis solutions [2, 3].

The Model-Based and Data-Driven techniques are the two basic FDD methodologies that are employed in PV systems [4]. In order to determine the relationships between a PV system's variables, including its parameters, model-based techniques use a logical model of the PV system [5]. The computation of residuals, which is used to assess the consistency of evaluated and assessed behaviors, forms the basis of model-based fault detection. These techniques have the primary advantage of requiring less hardware and working with different PV systems. Furthermore, these strategies be dependent on the mathematical model's ability to accurately describe the PV system's behaviors, in which more sense equipment is essential [6].

Therefore, fault classification, which works to categorize faults, is still quite difficult, specifically in large-scale PV systems [4, 7]. Numerous studies employing machine learning (ML) methods, that are data-driven methodologies founded on historic data gathered throughout PV system process, have focused on the FDD in PV systems [8,9]. ML is at the center of the artificial intelligence [10]. ML often involves memorizing rules from a vast amount of historical data using similar algorithms, making judgments or predictions based on new samples of data, and subsequently learning similarly to humans. Numerous machine learning methods have been used to identify and diagnose PV system faults [11, 12]. Artificial neural networks (ANNs) are one of the ML techniques, which are widely researched and used for fault diagnosis problems [13, 14]. The ANN approach offers an adaptable framework for education and identifying system faults by reason of the non-linear issues. Using a range of structures, the goal is to identify the relationship between the variable's input and output.

ANNs have become effectively used in fault detection of PV system and system modeling [15]-[18]. On the other hand, The ANN and other ML methods, rely on manually extracting features, which necessitates for diagnosis ability and a complete comprehension of database data. Additionally, manual feature extraction is also costly and time-consuming.

In order to diagnose a PV system, we advise employing Deep Learning (DL) algorithms, which can automatically extract features from raw data to overcome the issue of manual feature extraction. One of the most well-known applications of machine learning is deep learning (DL), which is used in many different fields [19]. It takes inspiration from initiatives to build and reproduce the neural network of the human mind to aid in analysis and training. The primary benefit of DL is its capacity for feature learning, which can suddenly identify complex structures and discover relevant features from layers of raw data. Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long-Short-Term Memory (LSTM) are currently employed for fault diagnosis with the aim of extracting the desired features. These methods try to extract features using, respectively, CNN, and LSTM networks. A softmax classifier is then used to classify faults using the features. When compared to more established shadow machine learning techniques, DL has produced good results, although its use in problem diagnosis is still in its early stages. In order to detect faults in an emulated Grid-Connected PV (GCPV) system, this paper offers FDD-based deep learning (DL) algorithms.

The rest of this paper is orderly as follows: Section 2 provides a brief description of the proposed DL techniques including ANN, CNN, and LSTM. Section 3 includes a description of the experimental materials, where the primary results are shown in this section, along with an explanation of the system and the data gathered during the examination. In section 4, the paper is concluded.

2 Deep Learning Techniques for Fault Diagnosis

This study deals with fault diagnosis of real GCPV system under various operating modes using deep learning techniques including: artificial neural network, convolutional neural network and long short term memory, which are discussed in details in the following subsections. The overall working principle of the proposed approach is illustrated in Fig. 1.

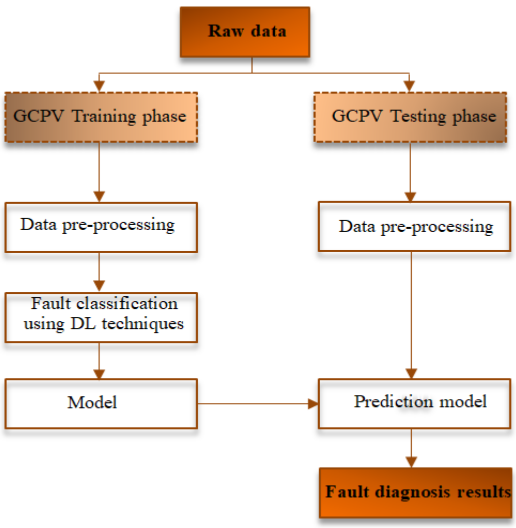

Fig. 1. Flowchart of deep learning approaches for GCPV fault diagnosis

2.1 Artificial Neural Networks (ANN)

ANN appeared effectively connected for both fault detection and system modeling [17]. The non-linear issues of the ANN approach provide an adaptable component for learning and identifying system faults. We have the fundamental Neuron Model and feed-forward architectures, which are utilized to determine the relationship between the parameters for both input and output. Fig. 2 shows a typical architecture, which also shows connections between neurons. Each link has a weight assigned to it, which is a number. In the hidden layer, the output of *ith* neuron is h_i [20].

$$h_i = \sigma\left(\sum_{j=1}^{N} W_{ij} x_j + T_i^{hid}\right) \tag{1}$$

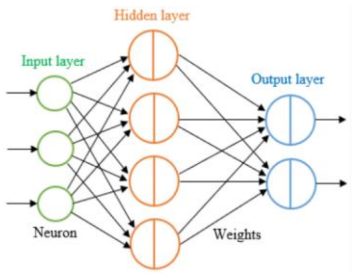

Fig. 2. Architecture of artificial neural network model.

2.2 Convolutional Neural Network (CNN)

The CNN is a supervised deep learning algorithm. It belongs to a type of deep learning networks (DNN) that are frequently used in computer vision and automatic language processing. It contrasts from convolutional neural networks in that its employments convolution in layers the matrix multiplication used in the classical method. It has topology like ANN with three layers specifically input layer, hidden layers and output layers. The hidden layers are an important part of CNN which consists of numerous hidden layers, and incorporates several convolution layers and pooling layers. The fundamental structure of the convolutional neural network is shown in Fig. 3. It is composed of two parts: Feature extraction part and classification part [21].

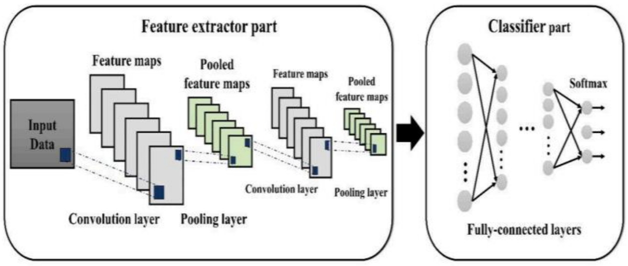

Fig. 3. Architecture of convolutional neural network

The first part works as a feature extractor for data. It contains input layer, convolutional layers (CLs), and pooling layers (PLs), which are stacked layer by layer in the network. The input data matrix is passed through a progression of filters, creating new feature called feature maps. Then, the convolution maps are flattened and concatenated into a feature vector, called CNN code. This CNN code at the output of the convolutional part is then connected to the input of a second part, made of fully connected layers (multilayer perceptron). The classifier part dedicated for fault classification and composed of a fully connected layer (FC) and an output layer. The FC layers receive the features get the highlights gotten by the last pooling layer as the input. The output is a last layer with one neuron per category. The numerical values obtained are as a rule normalized between 0 and 1, sum 1, to deliver a likelihood distribution over the categories.

2.3 Long Short Term Memory (LSTM)

LSTM is an improved extension from recurrent neural network (RNN) [22]. The primary distinction between LSTM and RNN is that LSTM can handle long-term dependence issues and successfully handle energetic information by utilizing a novel architecture cell that allows neural networks to filter information, leaving only useful information, and rejecting unnecessary information [23]. Although it has been used significantly to identify various dynamic systems, relatively little of it has been used to diagnose faults.

The LSTM contains many gate layers with the aim of forgetting information from memory. Instead of using one neural node with a nonlinear function such as in the case of RNN, new information is saved in memory and outputted as it advances through time. For each repeating module of the LSTM, there are four components: an output (o_t), an input gate (i_t), a forget gate (f_t), and a memory cell (c_t). The basic architecture of LSTM is shown in Fig. 4.

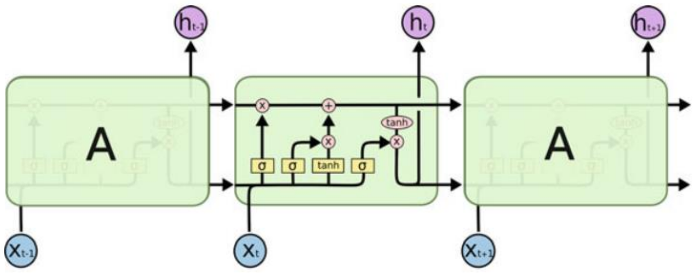

Fig. 5. Architecture of long short term memory cell.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{3}$$

$$c_t' = tanh(W_c[h_{t-1}, x_t] + b_c) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot c_t' \tag{5}$$

$$h_t = o_t \odot tanh(c_t) \tag{6}$$

Where all, W and b denote the weight matrices and bias terms. And the operator $\odot$ indicates the element-wise vector multiplication.

First, the new input x_t and previous hidden state h_{t-1} are used to obtain the forget gate f_t at time step t. Information from the last memory cell c_{t-1} shall be kept and vice versa if the value of the forget gate is less than 1. Second, an input gate formed from the new input and previous hidden state will be inserted into a memory cell so that it becomes c_t. Lastly, what should be taken from memory cells to create the new hidden state will be decided by the output gate.

3 Simulation results

3.1 PV implementation and data collection

We used the PV data and associated parameters from the earlier work in the current study [24]. Fig. 5 represents the synoptic of the GCPV system under study, wherever data collection and validation were carried out using a PV array and a Grid emulator [24]. Experimental faults discovered using the GCPV system simulator are those that are taken into consideration in this work. The Experiment was conducted by changing and injecting faults in various components to disable the normal operation of each part that construct the circuit. To ensure a comprehensive examination and study, these faults are injected at several levels (sensor, actuator, grid connection, PV panels, etc.) and locations (internal, external). After a brief period of normal operation, the faults are injected, and the predicted fault injection time is recorded for each fault so that the detection delay can be calculated. Depending on the type of faults and how frequently they occur, the recording time can be anywhere between 5 and 15 seconds. The sample period is 100µs. These faults are summarized in Table 1.

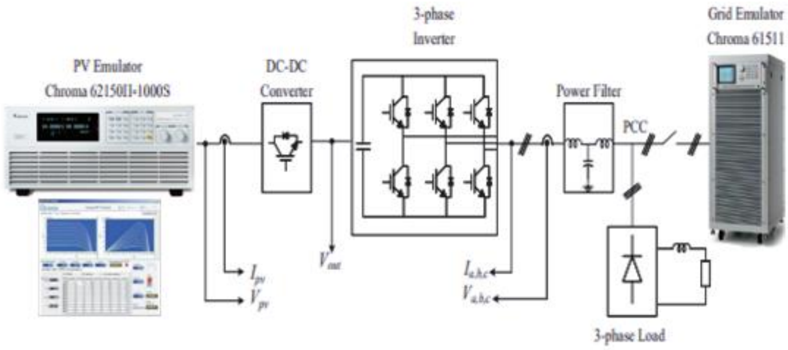

Fig. 5. Grid-Connected Photovoltaic system block diagram

Table 1. Description and characteristic of the different labeled Faults injected in the system.

Fault side	Fault type	Fault label	Fault description
DC side	PV Sensor Fault	Fault 2	Damage, malfunction or poor connection of the current sensor at the PV output.
	PV array level Fault	Fault 4	Permanent partial shading of 10% to 20%.
		Fault 5	Critical external fault due to loss of connection.
AC side	Three-Phase Inverter Fault	Fault 1	Damage of one IGBT at a time among the total of 6 IGBTs inside the three-phase inverter.
	Grid External Connection Fault	Fault 3	Critical external fault at the grid output level. This can be caused by loss or poor grid connection, sudden grid disconnection. The system will switch to a load for protection reasons.

In Table 2, the functioning of the investigated GCPV system is shown for one healthy case (marked for class C_0) and five different faulty operating modes (designated for classes C_1 to C_5).

Table 2. Construction of database for fault diagnosis system

Class	State	Training samples	Testing samples
C_0	Healthy	7000	2000
C_1	F1	7000	2000
C_2	F2	7000	2000
C_3	F3	7000	2000
C_4	F4	7000	2000
C_5	F5	7000	2000

3.2 Fault classification results

In order to assess the effectiveness of DL algorithms, the data collection collected out of the PV system was first divide into three groups namely, the training, validation, and testing datasets. According to the partition ratio of 0.7 used in the process, the dataset is divided into training data with 70%, validation data with 10%, and testing data with 20%.

In this paper, many classifiers are tested. For the classification of faults with different nature, all techniques have good accuracy, in fact the NN gives accuracy over the testing phase of 94.55% with processing time of 1.5(s), the LSTM model was determined 95.12% in the testing data set with 2.84 (s), the last method is CNN where the accuracy in the testing phase is reached about 61.24%, respectively, with a computation time about 26.89(s). Actually, as reported in [25], the accuracy of CNN applied to fault diagnosis is not very high. A summary of the performance during the testing phase is shown in Table 3 based on accuracy and computation time (CT).

Table 3. Fault classification performance of proposed methods

Methods	Accuracy (%)	Processing time (s)
ANN	94.55	1.5
LSTM	95.12	1.65
CNN	61.24	26.89

The confusion matrices (CM) are indicated in Tables 4, 5 and 6. They're used to further assess the proposed approach effectiveness. For healthy class and faulty ones, the CM show the correct and misclassification of samples. The x- and y-axes are used to calculate predicted process statuses and true classes, respectively. For example, the NN technique (see Table 4) identifies 1761 samples out of 2000 (true positive) for the healthy case, which is assigned to class C_0. Of these, 1761 samples are considered to be faulty, while 4 observations are assigned to class C_1 and 235 measurements are assigned to class C_3. The NN classifier recognizes, among 2000 samples, 1983, 1964, 1822, 1997, and 1819, respectively, for the faulty cases (C_1 to C_5).

Table 4. Confusion matrix of ANN in testing phase

True classes	Predicted classes						Recall (%)
	C_0	C_1	C_2	C_3	C_4	C_5	
C_0	1761	4	235	0	0	0	88.05
C_1	3	1983	1	0	0	13	99.15
C_2	0	0	1964	0	0	36	98.20
C_3	167	9	1	1822	1	0	91.10
C_4	0	1	0	1	1997	1	99.95
C_5	0	99	82	0	0	1819	90.95
Precision (%)	91.20	94.61	86.03	99.95	99.95	97.32	**94.56**

Table 5. Confusion matrix of LSTM in testing phase

True classes	Predicted classes						Recall (%)
	C_0	C_1	C_2	C_3	C_4	C_5	
C_0	1720	7	0	273	0	0	86.00
C_1	2	1984	2	0	0	12	99.20
C_2	0	0	1974	0	3	23	98.70
C_3	107	13	1	1879	0	0	93.95
C_4	0	1	0	5	1993	1	99.65
C_5	0	98	44	0	3	1864	93.20
Precision (%)	94.04	94.75	97.67	87.11	99.70	98.11	**95.12**

Table 6. Confusion matrix of CNN in testing phase

True classes	Predicted classes						Recall (%)
	C_0	C_1	C_2	C_3	C_4	C_5	
C_0	975	1025	0	0	0	0	48.75
C_1	859	1141	0	0	0	0	57.05
C_2	0	0	1333	631	36	0	66.65
C_3	167	9	0	1900	100	0	95.00
C_4	0	0	0	1256	120	624	06.00
C_5	0	0	0	1	78	1921	96.05
Precision (%)	53.16	52.68	86.03	100.0	35.93	75.48	**61.58**

4 Conclusions

The issue of fault detection and diagnosis (FDD) for grid-connected PV (GCPV) systems is taken into consideration in this work. The methods that have been created are based on deep learning, using Experimental GCPV data representing various operating conditions. In the current study, we have classified DL based FDD into four categories: FDD based on Neural Network (NN), FDD based on Convolutional Neural Network (CNN), FDD based on Long Short Term Memory (LSTM). These methods have been tested and examined. The developed techniques generally demonstrated good monitoring and higher classification in terms of accuracy, recall, precision, and computation time. Moreover, the simulation results using a grid-connected PV system under both healthy and faulty situations demonstrated the effectiveness and robustness of the suggested FDD techniques.

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