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Unified Fuzzy Logic Based Approach for Detection and Classification of PV Faults Using I-V Trend Line

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Abstract: Solar photovoltaic PV plants worldwide are continuously monitored and carefully protected to ensure safe and reliable operation through detecting and isolating faults. Faults are very common in modern solar PV systems which interrupt normal system operation adversely affecting the performance of the PV systems. When undetected, faults not only cause significant reduction in the efficiency and life span of the PV system, but also result in damage and fire hazards compromising their reliability. Therefore, early fault detection and diagnosis of photovoltaic plants is a necessity for safe and reliable operation required for growing solar PV systems. Unfortunately, several recent fire incidents have been reported recently caused by undetected faults in solar PV systems. Motivated by this challenge, this paper, utilizing a proposed fuzzy logic algorithm, presents a novel technique for detecting and classifying faults in solar PV systems. Furthermore, the proposed method introduces fault indexing as a performance indicator that measures the degree of deviation from the normal operating conditions of the photovoltaic system. Various signatures of each fault scenario are identified in the shape of corresponding current-voltage trajectories and their extracted parameters. The effectiveness of the proposed technique is evaluated both in simulation and experimentally using a 5 kW grid connected solar array. It is demonstrated that the proposed technique is capable of diagnosing the occurrence of different faults with more than 98% accuracy.

Keywords: fuzzy logic controller (FLC); fault detection and diagnosis (FDD); machine learning (ML); photovoltaic (PV) systems

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1. Introduction

Over the past two decades, remarkable growth in the photovoltaic (PV) market has been seen due to relatively increased efficiency and reduced cost of PV modules. Significant power generation, around 115 GW, was recorded in 2019 [1]. With the increasing trend and reliance on photovoltaic systems, fault detection and diagnosis techniques have been becoming more critical for a safe and reliable operation of PV plants. Faults, such as crack, short-circuit, and open-circuit faults, cause undesirable impacts on solar PV systems including reduced efficiency and damage to PV facilities [2]. Short-circuit current and open-circuit voltage are affected due to shading, open and short-circuit faults. In addition to that, the open-circuit voltage can also be lower due to the effect of temperature. Additionally, the low short-circuit current may occur due to less irradiance, encapsulant damage, reduction in light trapping, and/or it may occur due to cracks. However, in this research work, reduction in light trapping and encapsulant damage are not considered because both are manufacturing and accidental mechanical defects and require a lot of external sensors. Several fault detection techniques have been proposed in the literature including a model-based approach, real-time difference method, output signal analysis, and machine-learning-based techniques such as deep-learning-based methods [3]. Among the listed methods, this paper focuses on machine and deep-learning-based techniques which are considered faster with greater accuracy reaching 91% [4]. The following reviews the literature of machine- and deep-learning-based fault detection techniques and classification at both module and array levels.

1.1. Machine-Learning-Based Fault Detection

An ANN algorithm was proposed for shadowing fault detection and demonstrated through a 3.15 kW PV system. A major limitation of the technique is its complexity and inability to be utilized for other types of faults [5]. ANN requires a large data set based on variations in input. In the case of open-circuit (OC) and short-circuit (SC) faults, the input conditions for the ANN become closer to binary, i.e., "fault is present or is not present". In open circuit faults the current becomes zero while in short-circuit faults the voltage becomes zero. ANN has a multi-layer operational procedure. The greater the input, the higher the accuracy will be. Therefore, it is obvious that the ANN will be computationally underloaded for detection of OC and SC faults because a lot of computational power and resources might be wasted. A Bayesian belief network was also used to detect various faults in grid tied PV installations in [6]. A fuzzy logic (FL)-based algorithm in [7] was presented for several abnormalities such as shading, water infiltration, and damaged diodes in addition to open-circuit, and line-to-line faults. The approach was evaluated and classified by the application of decision trees (DT) achieving an accuracy of 98.9% [8]. An artificial neural network (ANN) was also utilized based on three key parameters temperature, current, and voltage at the maximum power in [9] to detect shading, degradation, and short-circuit faults of a PV installation. An improved fuzzy logic approach was also proposed in [10] relying on measured increases in series resistance (R_s) providing binary results (yes/no).

A method for detecting arc faults was also presented in [11] relying on peak detection, frequency analysis, and observation of the operating point. In [12], module level temporal faults are identified by using a new introduced technique based on ANNFL with over 86% accuracy. However, line-to-line, line-to-ground, and short-circuit faults remain difficult to detect under low solar irradiance. In [13], shading, short circuits, and aging of PV installation are classified by the application of radial basis function–extreme learning machine (RBF-ELM) with an accuracy of 93.55%.

Short circuits and shading faults in PV installation are classified by using a fuzzy classifier based on theoretical parameters extracted from I-V curves in [14], with a classification accuracy of 95.3%. Abnormal aging, open-circuit and short-circuit faults are classified by using a LSSVM scheme in a Bayesian model and verified experimentally with an accuracy of 97.5% in [15]. In [16], the authors proposed a KELM procedure for identification and classification of partial shading, open circuit, short-circuit, and degradation faults of PV systems.

In [17], the authors proposed a multiclass SVM for identification and classification of abnormal degradation and line-to-line faults occurred at module level by using two different factors: fill factor (FF) and Kalman filter (KF). In [18], a PV system of 9.54 kW is subjected to two different probabilistic NN classifiers trained on a dataset of 11,840 readings, for detection of a disconnected and short-circuited panel through a reverse metering system. In [19], the authors implemented a C4.5 DT procedure, a kind of supervised learning, for detection and classification of short, circuited modules. In [20], a genetic algorithm is employed for identification and localization of open-circuit and short-circuit faults; however, its accuracy diminishes under different shading patterns. All the reviewed techniques above are limited by the size of arrays.

In [21], the authors employed a RFEL practice for detection and diagnosis of degradation, line–line, open-circuit, and partial shading faults. However, the proposed technique is not able to localize faults. In [22], the authors discussed the application of the KNN algorithm for detection and classification of partial shading, short-circuit, open-circuit, and line-to-line faults for a PV system of size 3 × 3. A comparative analysis of ANN and FL implemented on a 1.1 kW PV installation was presented in [23]. It has been concluded that the detection accuracy of ANN is better than FL, which is approximately 92.1%.

In [24], a fuzzy-logic-based offline technique is proposed to automate classification process of progressive faults such as delamination through thermal imaging techniques and ethylene-vinyl acetate (EVA) discoloring which is a challenging task due to the camera signal noise and atmospheric temperature variations. In [25], the authors proposed a graphical exponentially weighted moving average (EWMA) technique based on Shewhart and k-NN algorithms for detection of short-circuit, open-circuit, and temporary shading faults based on various parameters such as the current, voltage and power at the maximum power in addition to the irradiance and temperature. Short impacts of shading, open/short circuits, and snow covering on a PV installation have been investigated and faults are classified accordingly in [26], based on different parameters extracted from 720 I-V curves, which is a very complex process. In [27], three different classes of cracks for PV modules are detected and differentiated by using RF classifiers based on 735 electroluminescence images. A summary of the ML based techniques for PV fault detection including key contribution literature gaps is presented in Table 1.

Table 1. Applications of ML for PV installations.

Ref.	Technique	Contribution	Fault	Limitations/Research Gap
[6]	BBN	Detection	AC and DC faults	Multiple faults cannot be detected at the same time.
[7]	FL	Identification	Shading and broken cells	False detection of LL and LG fault under partial shading.
[8]	DT	Detection and classification	Line-to-line, open circuit, shading	Works only in limited scenarios.
[15]	LLSVM and Bayesian	Classification	Open circuit, short circuit and aging	Works only for small PV arrays.
[16]	KELM	Detection and classification	Line to line and open-circuit faults	Works better under uniform irradiance.
[17]	BPNN	Identification	Anomalies	False detection of LL and LG faults under partial shading.
[18]	Modified MLP	Identification	Shading fault	Not suitable for multiple shading patterns.
[19]	ANN	Localization	Short circuit	Takes lot of computational power and is very complex. Algorithm needs to be trained every time.
[20]	SVM-KNN	Classification	Short circuit	Can classify two faults.
[21]	ELM	Classification	Shading	Cannot classify multiple faults when occur at the same time.
[22]	NF	Detection	Increase in RS	It can only detect change in output current.
[25]	Fuzzy C mean	Detection and classification	Shading	It works only for shading faults.
[26]	DT (C4.5)	Detection and classification	Line–line, short and open circuits	Works for small PV arrays only.

1.2. Deep Learning Techniques

DL procedures are employed to resolve various problems of detection and diagnosis of faults, such as manual features extraction, single hidden layer, overfitting problems, low performance, and shallow ANNs. Conventional deep learning techniques particularly require large data sets of thermal or electroluminescence images [28–34].

Various DL algorithms have been found more effective in pattern recognition of fault images and their classification accordingly. In [35], faults such as snail trails, yellowing, delamination, gridline corrosion, and dust-shading are detected, classified, and localized by the application of DCNN and SVM on 7560 PV images obtained through unmanned aerial vehicles.

Line–line and open circuits of PV installation are identified on the basis of a dataset obtained through 2D representation of PV voltage and current and achieved high accuracy in [36]. In [37], partial shading, open-circuit, short-circuit, and degradation faults are detected and diagnosed by using a CNN with 2D ResNet, but a large data set is required for detection. Table 2 presents a brief overview of different deep leaning algorithms for fault detection.

Table 2. Applications of DL for PV installations.

Ref.	Technique	Contribution	Fault	Limitation/Research Gap
[35]	DCNN	Classification, localization	Yellowing, shadowing, snail	Large data set is required.
[38]	CNN (VGG-16)	Detection	Anomalies	Cannot detect multiple faults at a time.
[39]	DCNN- MC-SVM	Detection, identification	Yellowing, delamination, snail trails, dust-shading	Cannot detect short-circuit and open-circuit faults.
[37]	RestNet	Detection, identification	Short circuit, open circuit, degradation	Large data set is required.
[40]	DCGAN and CNN	Identification	Arc	Works only for ARC faults.
[41]	LSTM	Classification	Line-to-line, hotspot	Does not work under different shading patterns.

The major contribution of this research work is as follows:

- Faults are detected and classified in both series parallel and total cross tied configuration.
- Existing fuzzy logic techniques are employed for detection of a single fault at a time. Our proposed approach addresses the issue by detecting multiple faults at a time.
- The proposed approach is applicable for large systems.
- This research work proposes, for the first time, a fault index based on a linear trend line-based approach which makes detection accurate and simple.
- This research work establishes a data set of a PV system of different faults with different severity levels.
- This technique classifies faults based on severity levels, so that the relevant protection scheme can be adopted accordingly.

2. Methodology

This section presents the proposed fuzzy-based fault detection method which is illustrated in the flowchart of Figure 1. As shown, the first step for implementing the proposed technique is the establishment of data sets both through simulation and experimentally. The system used for this purpose consists of a 6 $\times$ 6 PV array connected to the grid. Each module rating is 150 W with manufacturer datasheet parameters presented in Table 3. The used PV modules are of the type "TDB125x125-72-P 150W" manufactured by Ningbo Solar Electric Power.

For data collection, different faults such as shading, open-circuit and short-circuit faults covering a broad range of severity levels and locations are employed for the PV system for two different configurations: series-parallel (SP) and total cross tied (TCT) configurations. Specifically, three different severity levels of the stated faults are used. Because the outputs of the array including the open-circuit voltage, short-circuit current, and power are affected by the type, severity, and location of faults, the resulting outputs are recorded accordingly under all fault scenarios creating a comprehensive dataset for training. The data includes *I-V* trajectory collected for each fault scenario.

The same practice is repeated with the experimental setup of a 5 kW PV system connected to the "Fronius" inverter, depicted in Figure 2, which is used for storing the needed parameters. The data is collected with milli-scale variation. Shadow fault was implemented through covering the system with different sheets of several opacity levels. Open-circuit and short-circuit faults were applied through intentional cutting and shorting of connections at multiple locations.

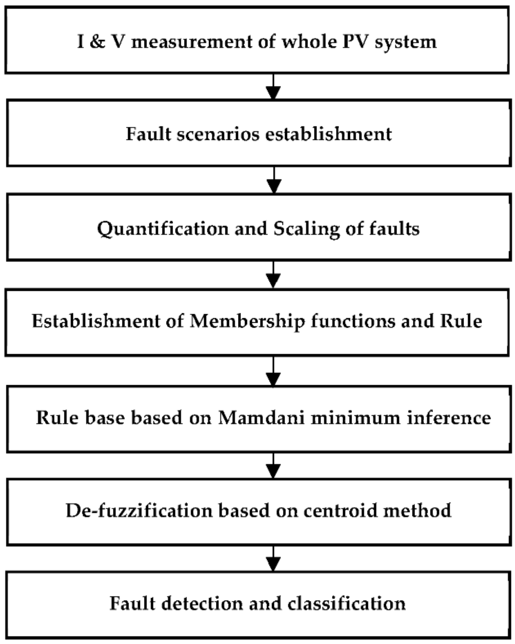


Figure 1. Process flow of the experimental setup.

Table 3. PV array block parameters (Ningbo solar electric power (Mono)).

Power (STC)	150 W	Cells per Module	54
Open-circuit voltage	43.4 V	Short-circuit current Isc	4.86 A
Voltage at MPP	35.2 V	Current at MPP	4.26 A
Nominal cell temperature	47.2 °C	Temperature coefficient of Isc	0.06

The second step is quantification and scaling of faults. The maximum and minimum limits of design parameter are quantified and scaled. Voltage at the maximum power point is taken as one parameter, because each fault results in different V_{mpp} for different severity levels. In the proposed technique, *I-V* trajectories/curves of the PV array under various faulty conditions are subjected to the calculation of a newly introduced parameter 'fault index'. The value of 'fault index' is calculated through the linear interpolation of *I-V* trajectories and power at the maximum point of the PV array.

Figure 2. Pictorial view of the experimental setup of 5 kW.

Critical analysis of *I-V* trajectories, while focusing the basic criteria of the curve fitting technique, plays a pivotal role for the application of the proposed technique. A linear trend line trajectory is employed prior to the maximum power point as the slope of the *I-V* curve is insignificant near the short-circuit current and it decreases negatively towards the bottom of the curve. The exponential trend line for the complete *I-V* curve of the PV array requires higher order equations which can result in over fitting of the curve and increased complexity; therefore, a linear trend line is preferred. Experiments were conducted on an already installed PV system with a power rating of 5 kW and an open-circuit current capacity of 40 Amps. The commercially available IV tracer has a current rating of 15 Amps. In addition to the above-mentioned reason, our proposed methodology V_{mpp} is taken as one of parameter which is directly taken from the inverter. Whereas the fault index is formulated by multiplying Pmp with the slope of the IV trend line. The IV trend line is established by manually changing the load for three instances.

The trend line against different fault scenarios can be calculated using (1) while the value of the fault index is calculated through (2).

$$m = \frac{instantenious\ change\ in\ current\ (\Delta_n I)}{total\ change\ in\ Voltage\ (\Delta V)} \tag{1}$$

$$i = -m \cdot Pmax \tag{2}$$

where

i = fault index;
m = slope of trend line;
P_{max} = maximum power of PV array;
m is the slope of the trend line.

The change in voltage is recorded against each instantaneous interval change in current. The concept of linear interpolation is followed for establishing a trend line. After finding slope of the trend line, it is multiplied with power at the maximum point yield's fault index. The fault index is the severity of a fault. This is variable is introduced for the first time. The discerning values of fault indexes and power at maximum power point are the key parameters which are subjected to the fuzzy logic controller for classification of various PV faults. Slopes between each consecutive data point of the data set are taken and then added incrementally until the maximum power point.

The third step includes producing input and output membership functions. Depending upon the variation pattern of the *I-V* trajectories, triangular membership functions are used to represent mentioned parameters. Input membership functions consisting of different values of the fault index (i) and V_{mpp} are generated for fuzzy logic inference engines. Output membership functions based on the diagnosis rules set are defined for detection and classification of open-circuit, short-circuit, and shadowing faults.

Next, a set of rules are established where fuzzy "if–then" rules are defined in the fuzzy editor based on the boundary range and quantity of membership functions. Apropos, fault indexes are divided into four different classes including very low (VL), low (L), medium (M), and high (H), whereas values of V_{mpp} are divided into three different sections including low (L), medium (M), and high (H) for the formulation of fuzzy rule sets shown in Table 4.

Table 4. Fuzzy rule set.

R1	if (Fault_Index is M) and (V_{mpp} is H) then (PV_Fault is NF)
R2	if (Fault_Index is VL) and (V_{mpp} is L) then (PV_Fault is OCF)
R3	if (Fault_Index is H) and (V_{mpp} is M) then (PV_Fault is SF)
R4	if (Fault_Index is L) and (V_{mpp} is H) then (PV_Fault is SCF)

Finally, a defuzzification is conducted where the Mamdani algorithm of fuzzy logic control with the 'centroid' defuzzification technique is employed. These steps guarantee generating accurate results as they deal with ranges of the different parameters rather than data points for shadowing faults which have different severity levels.

3. Results and Discussion

The output power of the standard PV array (6 × 6) harnessed using "Ningbo Solar Electric Power TDB125x125-72-P 150W" connected in SP and TCT configurations, is approximately 5.4 and 5 kW, respectively. Characteristic curves of PV arrays under different faulty conditions are generated through MATLAB/Simulink to observe the impacts of faults in SP and TCT configurations.

Fuzzy input membership functions are formulated by using the fault index ranging from 19.16 to 130.82 and voltages at maximum power point ranging from 178.54 to 231.17. The discerning values of the fuzzy output membership function obtained against respective combinations of fault indexes and V_{mpp} can classify the operating condition of the PV array. Output values of the fuzzy logic controller classifying the operating conditions of the PV array are shown in Table 5. Moreover, the fuzzy rules view for classification of PV faults is shown in Figure 3. Parameter ranges of the fault index (i) and V_{mpp} against different operating conditions of the PV array are given in Table 5. Moreover Table 6. Shows the results in tabular form.

Table 5. Classification of PV faults.

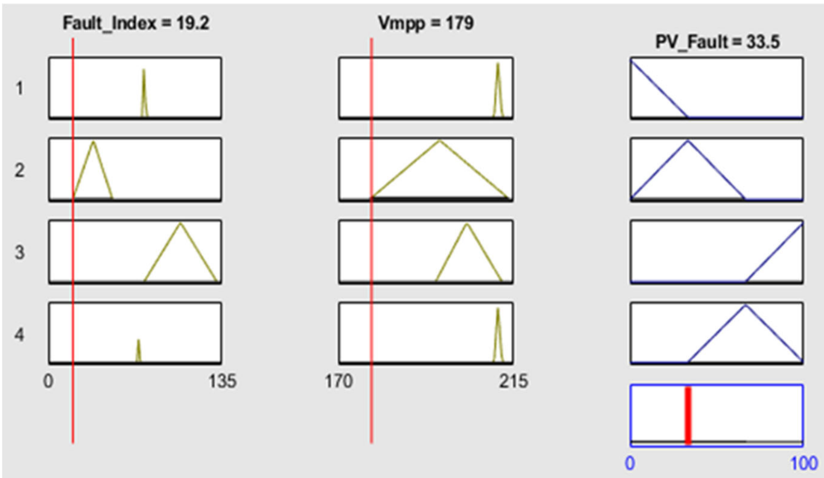
Type of Fault	Fuzzy Results
SP Configuration	
No Fault	11.3
Open-Circuit Fault	33.5
Short-Circuit Fault	50
Shading Fault	83.5
TCT Configuration	
No Fault	5.9
Open-Circuit Fault	39.2
Short-Circuit Fault	58.6
Shading Fault	88.3

The results are shown in Figures 4 and 5, respectively. Figure 5c also shows examples of data points for the calculation of "m". Significant behavioral changes in characteristic curves of PV arrays arranged in two different test scenarios are concluded as follows:

- **SP Configuration:** Short-circuit faults introduced in SP exhibit less impacts on power and current values as compared to open-circuit faults. However, shading faults show non-uniform behavior with abrupt reduction in both power and current values. In the case of open-circuit faults, short-circuit current reduces abruptly where during short-circuit faults the open-circuit voltage decreases sharply. The SP configuration is more susceptible to open-circuit faults than short-circuit as shown in Figure 5.

- **TCT Configuration:** Open-circuit faults cause a non-uniform pattern of reduction in power, whereas abrupt voltage drops are observed due to short circuits. Moreover, shading faults result in abrupt reduction of current and power with a high ripple effect. Overall, the TCT configuration is less impacted by shading faults in comparison with the SP configuration during shading.

Finally, it is important to mention that non-uniform distribution of collected current, thermal runaway, and capacitive effects cause kinks in *I-V* and *P-V* curves. Whereas shading produces multiple power peaks in the PV curve of normal PV arrays, but the above-mentioned factors affect the shaded PV curve with kinks and uniform reduction. There are multiple factors which deviate IV and PV curves such as insolation, tilt angle, snail fault (cell cracks), failure of bypass diodes, interconnection failures (open circuit and short circuits), and degradation. In this research work, three major factors are addressed which underlay almost all other factors. For example, interconnection failures, cell cracks, and bypass diode failures are subcategories of internal open-circuit and short-circuit faults. In an open-circuit fault the connection/line breaks while in short circuit it shortens. While external faults are inter- or intra-string/array faults.



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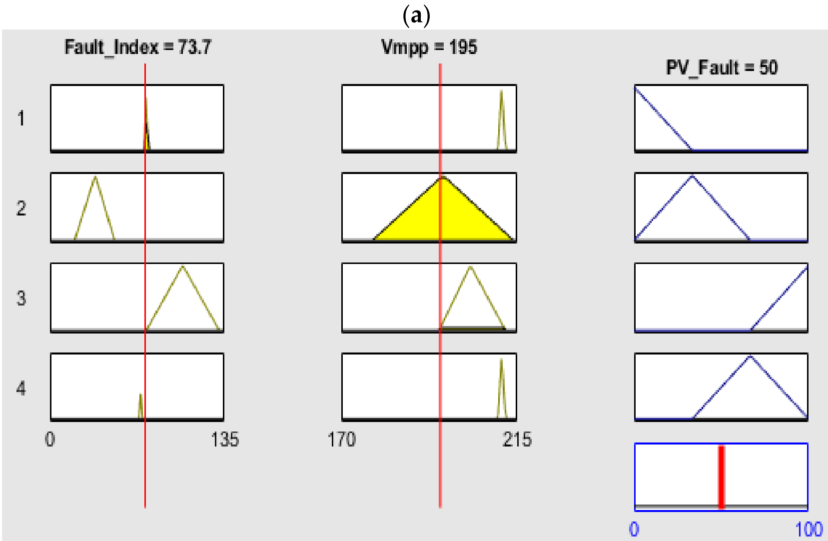

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Figure 3. *Cont.*

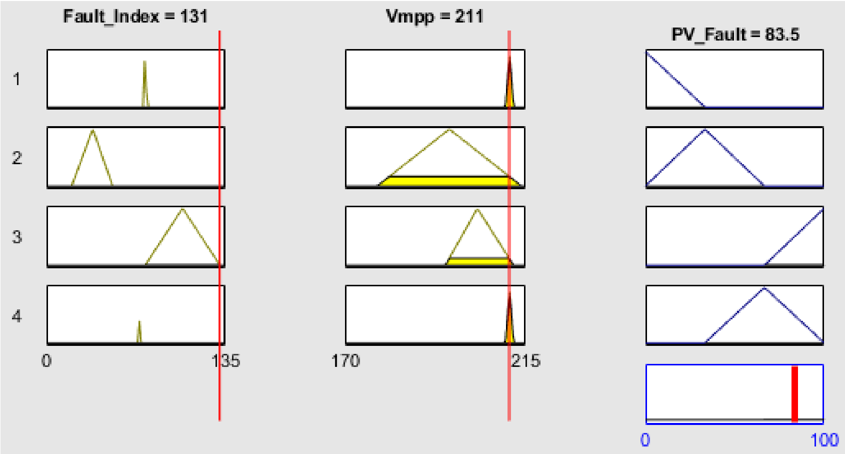

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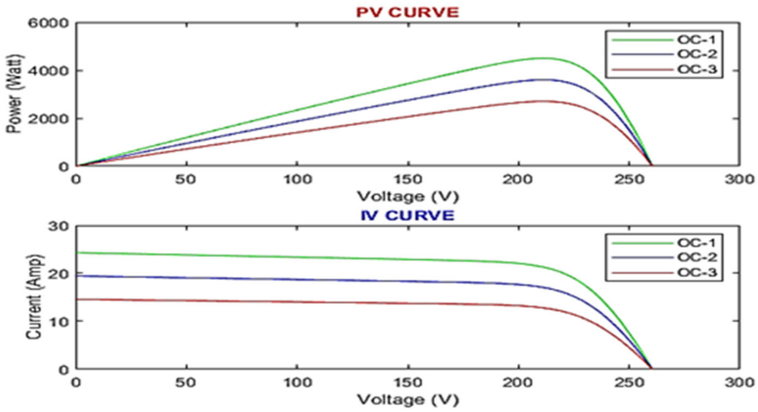
Figure 3. Fuzzy rule view. (**a**) Open-circuit fault. (**b**) Short-circuit fault. (**c**) Shadowing fault.

Table 6. Classification of PV faults.

Operating Condition	Fault Index (*i*)	V_{mpp}
Normal Operation	71.24	210.72
Open-Circuit Faults	19.16–49.93	178.54–231.17
Short-Circuit Faults	73.66–75.02	195.29–211.34
Shading Faults	66.70–130.82	210.88–211.39



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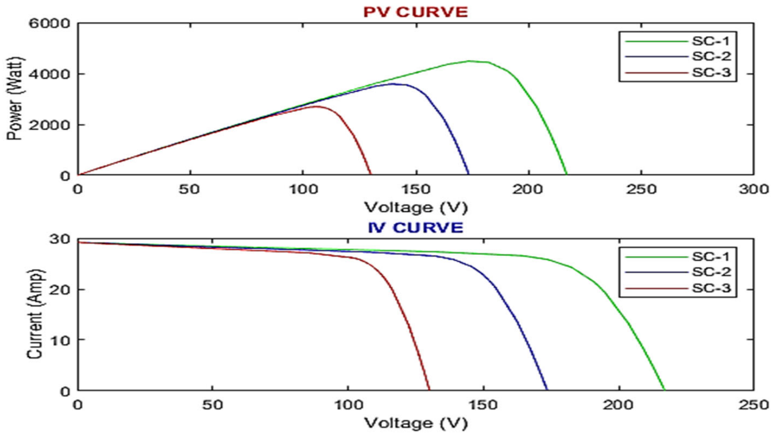

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Figure 4. *Cont.*

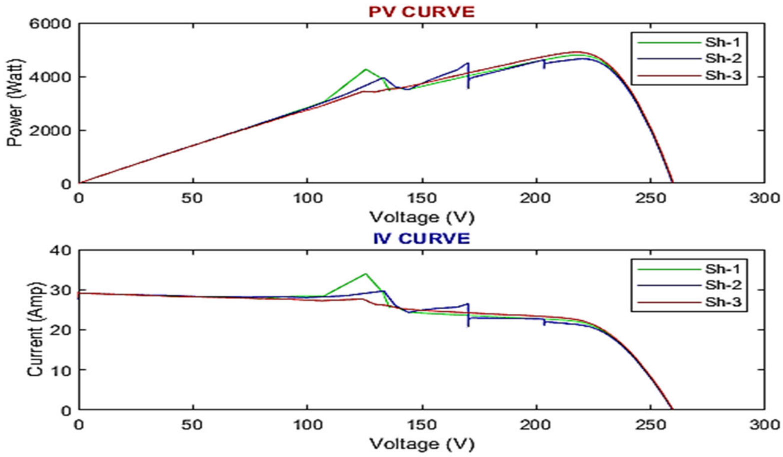

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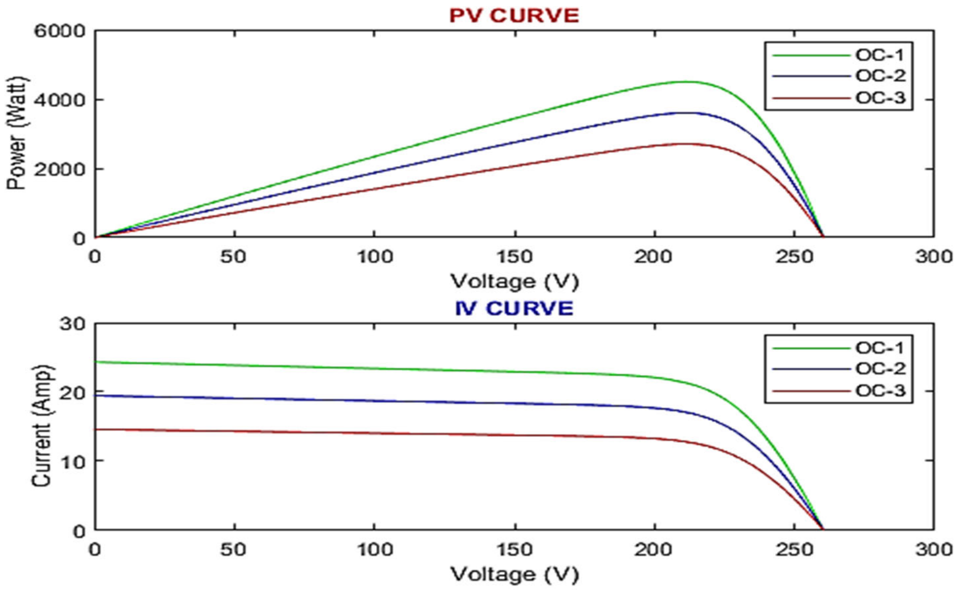
Figure 4. Impact of fault on TCT configuration. Open-circuit fault. (**b**) Short-circuit fault. (**c**) Shadowing fault.



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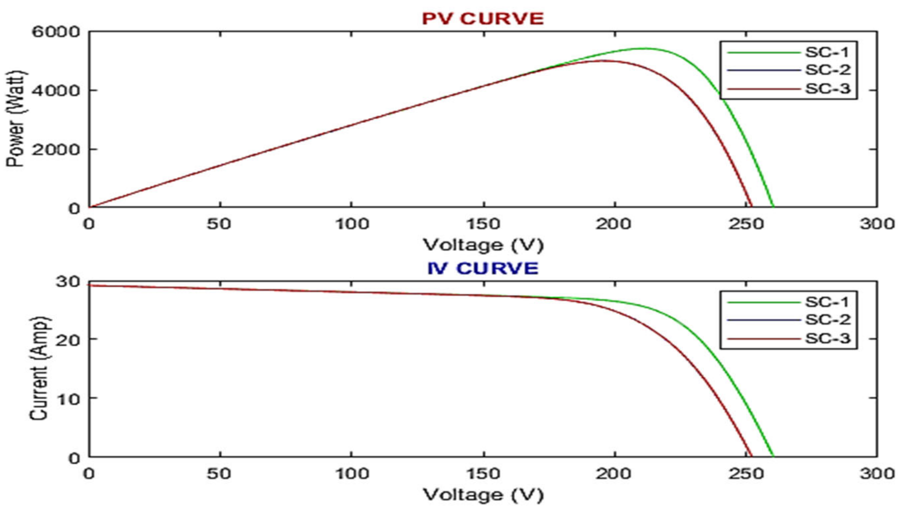

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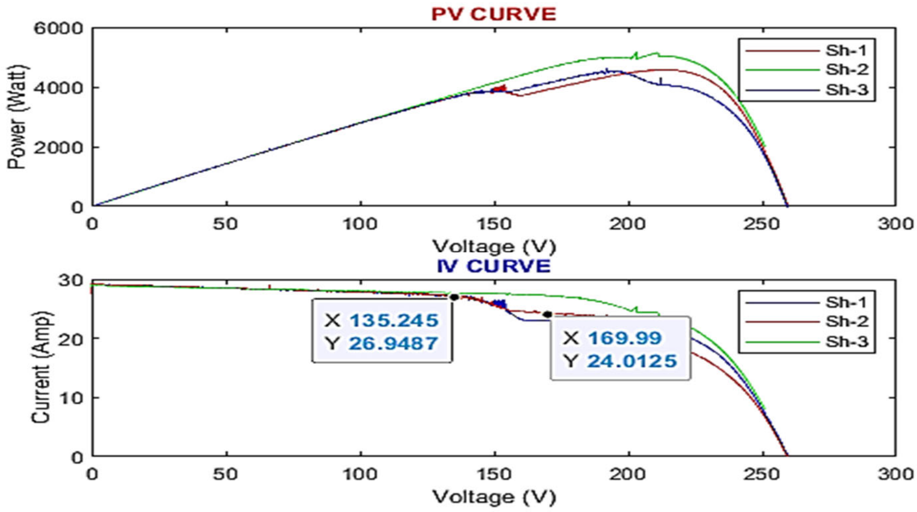
Figure 5. *Cont*.



(**c**)

Figure 5. Impact of fault on SP configuration. (**a**) Open-circuit fault. (**b**) Short-circuit fault. (**c**) Shadowing fault.

4. Conclusions

The aim of this research work was to devise a novel and simple technique for detection and classification of most common faults occurring in solar PV systems by using a fuzzy logic controller. A novel technique based on linearity of I-V trajectories obtained through varying intensity and location of faults introduced in a PV array was used for extraction of key parameters, which were further used for calculation of a newly introduced parameter 'fault index' which measures the degree of deviation from the normal operating conditions of the PV system. The electrical parameters extracted through the proposed technique were subjected to a fuzzy logic algorithm for classification of faults. It was verified through simulation and experimental setup of a 5 kW grid tied solar PV system that can detect and classify all common faults using the proposed technique. The proposed method is efficient and quite easy to implement as compared to other techniques which usually require a large data set for training of algorithms.

The discerning values of fault index ranging from 19.16 to 130.82 obtained through the application of proposed technique remarkably diagnose the occurrence of various PV faults, achieving an accuracy of 98% with an average decreased error of 13% compared to other conventional fault diagnosis techniques.

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Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
DL	Deep Learning
DT	Decision Tree
DCNN	Deep Convolutional Neural Network
FLC	Fuzzy Logic Controller
GNN	Generative Adversarial Network
IoT	Internet of Things
KELM	Knowledge Enhanced Language Model
KNN	k-Nearest Neighbor
LSTM	Long Short-Term Memory
LSSVM	Least Square Support Vector Machine
MPPT	Maximum Power Point Tracker
MLT	Machine Learning Technique
NF	No Fault
OCF	Open-Circuit Fault
OCPD	Over Current Protection Device
PV	Photovoltaic
ResNet	Residual Neural Network
SP	Series-Parallel
STC	Standard Testing Conditions
SVM	Support Vector Machine
SSTDR	Spread Spectrum Time Domain Reflectometry
SCF	Short-Circuit Fault
SF	Shading Fault
TCT	Total Cross Tied
TDR	Time Domain Reflectometry
VGG	Visual Geometry Group

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