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A novel intelligent detection schema of series arc fault in photovoltaic (PV) system based convolutional neural network

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ABSTRACT

Series Arc Fault (SAF) is the failure that occurs between any electrical contact and any electrical circuitry. However, it considered one of the common malfunctions that affect the operation of the PV system and causes serious problems such as fires and electrical shock hazards. Several reasons increase the possibility of this type of failures, such as incorrect installation, irregular maintenance, and some environmental effects. This paper presents a new intelligent and accurate detection method of SAF in the PV system. In this method, Convolutional neural networks (CNN) which is a discriminative (supervised) deep learning algorithm used for the process of fault detection. In typical cases, the signal consists of DC component, inverter component and noise of Network. In the case of SAF, a new part will add to the signal; therefore, CNN used to discriminate against the additional component to detect the SAF accurately. PSCAD is used to generate the Arc fault model; Performance evaluation and the results of the proposed method implemented using Python. The achieved accuracy of the proposed detection method is 98.9%.

Keywords: Series Arc Fault, Photovoltaic System, Intelligent detection algorithm, deep Learning, Artificial Intelligence, DC Arc Fault.

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1. Introduction

Electrical power can be generated from the sun using PV systems. Every year, there is a significant increase in the percentage of solar energy in the electric grid. The critical issues to the power grid and consumers are the safety and stability in the operation of the PV system [1-3]. Several reasons lead to creating the arc fault, for instance, improper connection, animal bites, rain, non-schedule maintenance and dissolution of cable insulation. Moreover, three types of arc faults can happen in the PV system according to the location of fault occurrence; the first one called parallel arc fault that forms between different poles such as positive and negative or different branches. The second one is ground arc fault, which can occur between any part of the system and the ground, the third one called series arc fault created in series with system parts. However, high current accompanied to parallel, and ground arc fault makes them easy to detect using the over-current method [4]. Series arc fault is more challenging to diagnose according to the little decrease in the line current after arc starting [5]. Early detection of arc fault as soon as possible leads to avoid risks associated with it. Therefore, in recent years, many researchers try to find efficient methods to detect a series arc fault [6-8]. In this regard, and to tackle the problem, there are many approaches presented.
In general, these approaches categorized into four different groups: remote detection methods, time-domain methods, frequency-domain methods, and hybrid methods.
The methods that depend on the thermal, electromagnetic and other spread waves from the solar farm belong to the remote detection methods [9]. [9] Presents a process of analyzing RF signal resurrected from the DC of a PV system. This category can suffer from a decrease in the reliability and performance according to plenty of noises in the PV system. Besides, another limitation considered when using these methods is the cost due to the need for additional equipment.

The methods which based on analyzing the random variations of voltage or current time-domain signals to detect series arc fault belong to the time-domain group. To identify the occurrence of a series arc fault, an entropy variation of the current signal selected [10]. In [11], the variance obtained from the filtered PV current analyzed to detect the series arc faults. The fluctuations and the flow of direction of the current are sometimes considered in several methods [12]. Nevertheless, these methods often sensitive to the disturbance of switching equipment and controllers like the maximum power point (MPPT). Also, depending on the selected threshold acts as another weakness.
Another group that vastly used in the process of series arc detection is the frequency-domain methods [10, 11]. A suitable sign for the detection process is the amplitude increase of the voltage and current in high-frequency components. The major weakness of these methods is the sampling frequency; furthermore, the existence of inverter disturbances in the associated bandwidth can result in adverse effects on these methods. [12] Proposed an approach of analyzing the signal in frequency-domain; [13] investigates a method of estimation for the frequency of the inverter switching. These methods faced some limitations in practice such as subject to the interference of switching and having a lack of estimation of the arc characteristics.
The last group of methods is a hybrid based on the characteristics of the signal in both the time and frequency domain [14]. The most familiar approaches of this group are short-time Fourier transform (STFT) that used the functions of decomposition signal in the frequency domain and wavelet transform as a tool of time-frequency domain [15-19]. [20] Presented a method of arc fault detection that use the spikes of voltage in the frequency domain associated with the fluctuations of current in the time domain. However, the noises of controllers such as MPPT and the unexpected change of the load can present a negative impact on these methods as the others. The methods that used artificial intelligence in the process of detection belong to this group [21]. These methods are difficult to employ according to some factors such as the non-interruptible results, complexity and the overhead of the computational [22]. This paper proposed a novel intelligent method of DC series arc fault detection based on Deep learning algorithms. Convolutional neural network (CNN) schema used to employ the proposed method of series arc fault detection in the PV system. Hyperbolic tangent approximation model used to generate the Arc fault signal.

1.1. Challenges

The accurate detection of the series arc fault in the DC is considered as a hard task due to many difficulties:
The PV system can continuously feed the power even the occurrence of the arc fault as daylight which leads to increase the fires and even electrical hazard shock.

The module of the PV system is considered as a current limited device; which means that the occurrence of any fault may similar to the behavior of the normal operation.

There is no zero-crossing point in the waveform of the DC; however, the existence of the zero crossing point in the AC waveform makes the process of series arc fault detection easier as compared with the DC that is more difficult to detect.

The existence of many joint among the conductors according to the size of the PV system and the series arc fault may occur at any one of them.

1.2. Contribution

The main contribution of the proposed method has been addressed as follows:
The creation of an effective and intelligent detection method that can precisely detect and diagnose the DC series arc fault-based convolution neural network (CNN) with less complexity and a high accuracy of 98.9%.
The proposed method increased the reliability and safety of the DC network protection due to the fast and accurate detection of the series arc fault.
The detection method can precisely discriminate between the exact series arc fault, the other fault that can occur in the PV system and the noise of the normal behavior.

2. Methodology

One of the most problems that can affect the operation of the PV system is the series arc fault. It can cause a series of dangerous problems such as fires and electrical hazards shake. Figure (1) shows the block diagram of

the methodology for the proposed method that detects the series arc fault in the PV system. It consists of a PV model, Arc Fault model, and the intelligent model of the series arc fault Detection.
The characteristics of the PV model used in the system are shown in table (1). The output of the Solar PV system which is the voltage and current measurement used in the process of series arc fault generation. However, the model of series arc fault generation and the construction of the dataset explained in more detail in section 2.1. After completing the process of arc fault generation, the output dataset normalized and used in the process of training the intelligent detection method. Moreover, one of the most common types of deep learning which is the CNN Schema used to process the task of detection where the proposed method explained in more detail in section 2.2.

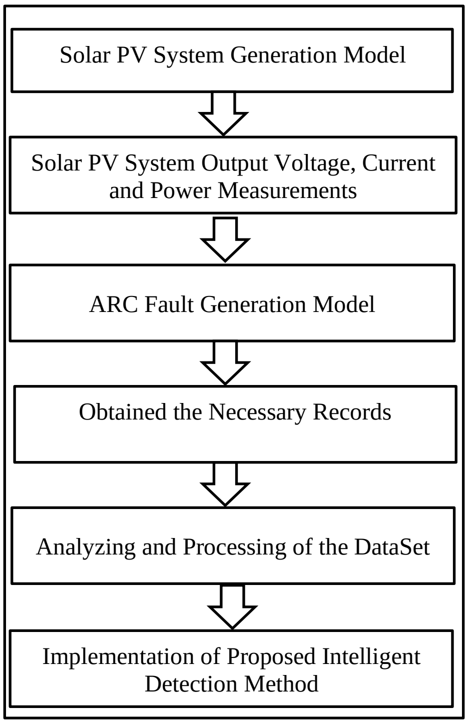


Figure 1. Block diagram of methodology

Table 1. PV modules characteristics

Model	Polycrystalline HN-20/36
Maximum Power	20 W
Voltage at P_{max} (V)	17.5 V
Current at P_{max} (A)	1.16 A
Open Circuit Voltage (V_{oc})	21 V
Weight (kg)	2.2
Dimensions	350 * 500 * 25

2.1. Constructing dataset

A large collection of a simulation dataset has been generated and collected based develop arc fault model that is independent of electrical time constants. The developed model is known as the hyperbolic approximation model; where the mathematical approximation of this model that is used to represent its characteristics has been shown in equation (1) to (5). Moreover, the circuit of this model which is shown in figure (2) consists of a dependent voltage source (egap) that is connected in series with a variable resistor (Rgap). The other parameters of this model are force pulse of electromotive (egap), gap of Current (igap), the measured distance from cathode to anode (xgap), the boundary between the phases, arc's burning and quenching, of the arc (xcrit), the average of DC voltage before the existence of the arc (Vdc), the slope controller variable vq (α) and slop of egap (λ). Also, the average of DC current before the existence of the arc (Iload), and two constant variables which are a and b.

$$e_{gap} = \frac{1}{2}\left(a + bx_{gap}\right)\left(tanh(\lambda q) - tanh\left(\lambda(q-1)\right)\right) \quad (1)$$

$$v_q = V_{dc}\left(\frac{1}{2} + \frac{1}{2}\left(tanh\left(\alpha(q-1)\right)\right)\right) \quad (2)$$

$$v_{gap} = v_q + e_{gap} \quad (3)$$

$$q = \frac{x_{crit}}{x_{gap}} \quad (4)$$

$$R_{gap} = \frac{v_q}{i_{gap}} \approx \frac{V_{dc}}{I_{Load}} e^{2\alpha(q-1)} \quad (5)$$

In more detail, a nearly rectangular pulse of amplitude (a + bxgap) is used to approximately generates the pulse of egap. However, the random characteristic of the arc is shown through the using of a relative parameter (q); where (0 < q < 1) and λ used to control the ratio at which egap increased and decreased.

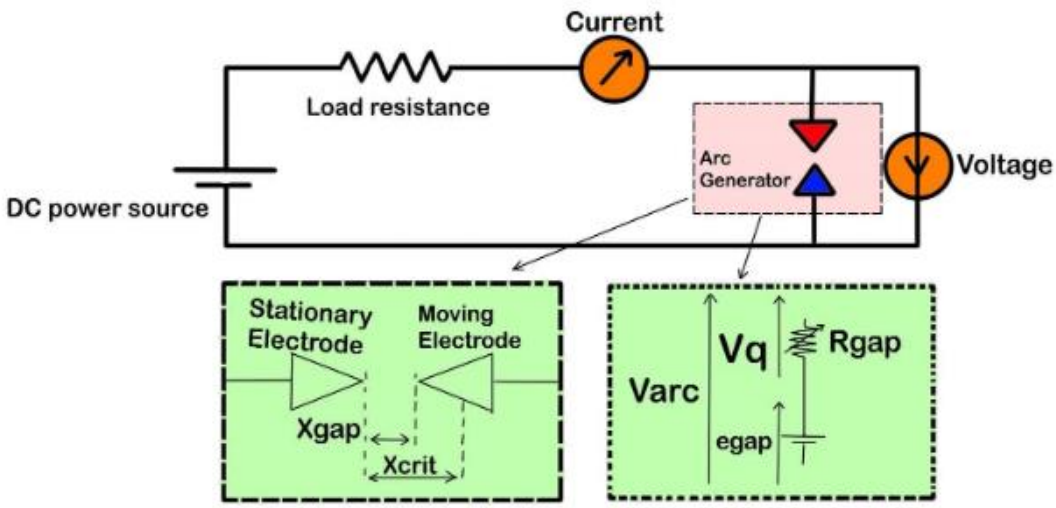


Figure 2. Equivalent circuit of the series arc fault model

2.2. Proposed intelligent detection method

In this section, the proposed intelligent detection method will be explained in detail; where the proposed method can precisely detect and diagnose the series arc fault in the PV system. A suggested Convolution neural network (CNN) schema-based deep learning algorithm used in the process of detection in the proposed method; where its architecture consists of sequential layers that can automatically extract all the necessary features based on the given dataset obtained from the arc fault model. Moreover, the use of non-linear transformation functions in the structure of the sequential layers presents more precise results in the process of detection.

In more detail, CNN schema like the standard neural network (ANN) except that it is used for the processing of large-scale data. It performs the operations of convolution to process the data in the multiple arrays through the use of certain filters with specific stride. However, the standard ANN consists of three main layers which are input, hidden and output layers. Each layer contains a number of the neuron where each one of them can only receive the data from the previous layer and send it to the next layer. This network can be considered as multiple complexes of simple nonlinear functions ranging from input to output space [23, 24].

For an array of Two-dimensional (2D) input (IN) and one channel, the size of filters (k) Rf × Cf and the size of the step S=1, the size of the feature map for the output is Hi×Wi, the operation of convolution for each filter, can be computed from equation (6):

$$OUT_K(h_i, w_i) = \sum_{i=0}^{R_{f-1}} \sum_{j=0}^{C_{f-1}} IN(s * h_i + i, s * w_i + j) * W_k(i,j) + B_k \quad (6)$$

Where B is the coefficient of bias and W is the coefficient weight of the matrix. The index output of the row and column of the 2D array is represented with, respectively. The maximum value of a specific square area according to the kernel size of the max-pooling is only kept in the max-pooling layer. And, it is usually computed after the CNN layer to decrease the dimension of the output. Thus, the key information of the features extracted by the CNN layer can be conserved with the decreased computations [25, 26]. The activation layer which is the leaky rectified linear unit (Leaky ReLu) that used to reduce the problem of the gradient vanishing is shown in equation (7) [26]:

$$f_{Leaky\ Relu}(x) = \{ \begin{matrix} 0.01.x\ , & x \leq 0 \\ x & x > 0 \end{matrix} \tag{7}$$

It is often the process of minimizing the cross-entropy as much as possible to reach 0 occurs through the optimization procedure of the CNN with training an amount of data; the loss function of the categorical cross-entropy that occurs in the case of multiple classifications and depend on N size of the batch of data is named as LOSS and can be stated as shown in equation (8):

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{ik}\, lg\, \frac{e^{x_{ik}}}{\sum_{k}^{K} {}_{1}e^{x}{}_{ik}} \tag{8}$$

Where x_{ik} and y_{ik} represent the last layer expected output and the label of truth category, respectively. The algorithm of dropout [27] is often used to enhance the performance of generalization of the network. Batch normalization [28] is incorporated to prevent internal covariate shift, hence avoid over-fitting issues in network training [29]. The flowchart of the detection method is shown in figure (3).
This network is well-trained by adopting the categorical cross-entropy as the loss function and Adam optimizer [30] to update network parameters in the backpropagation.

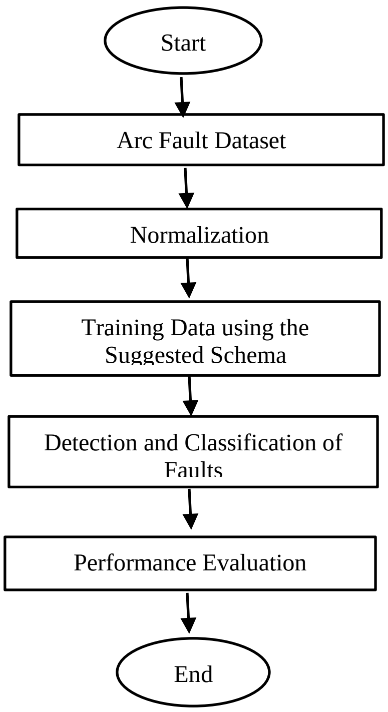


Figure 3. Flowchart of detection method

3. Results and discussion

The system consists of two main parts: the first part was the generation model of the series Arc fault to obtain the records that used for the process of training of the proposed schema. The second part is the suggested CNN schema that trained to classify the types of faults and accurately detect the series arc fault.

3.1. Arc fault generation model

Number The generation of arc fault model was simulated using PSCAD software as shown in figure (4). The generated model based on the hyperbolic model that takes into consideration many different cases through changing different factors such as the length of the arc, irradiance, the frequency of inverter switching, the current of load, and temperature. These criteria were adopted to obtain better results and producing a large number of records that covered all the predicated cases of fault that can face the PV system. Moreover, the produced records can be classified into:

- **a.** A group of records that dedicated to the inverter startup
- **b.** A group of records that represent load setup change.
- **c.** A group of records that shows the series arc fault.
- **d.** A group of record that indicates to the other arc fault.

The total generation records were approximately 800 records with 6000 data points. The generated records are normalized according to a specific window length and after completing the process of samples normalization the process of training data using the suggested schema will be started to create the detection method.

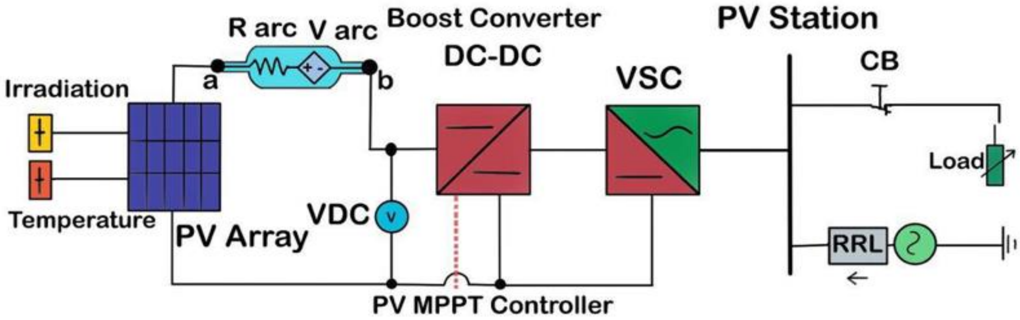
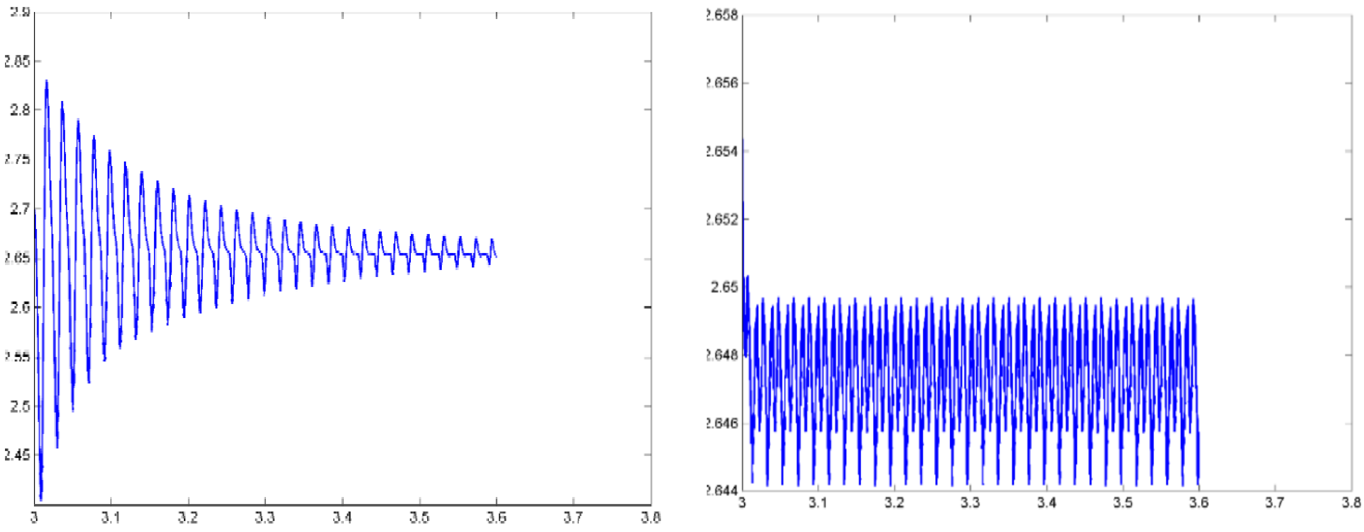


Figure 4. Circuit of Series arc fault model

3.1.1 Dataset of inverter startup and load setup change

This dataset has been collected form the generated arc fault model to represent two important case that can be considered as a normal behavior in the PV system. The first one is the inverter startup that can be defined as the method of the solar power three phase starting. The load change can be considered as the second normal behavior of the PV system. The occurrence of the inverter startup and/or load change leads to a fluctuation in the output voltage of the PV system which is varies according to these factors. Figure (5) shows several samples of inverter startup and load change.



(a) (b)

Figure 5. Samples of the normal case: (a) Sample of inverter startup; (b) Sample of load change

3.1.2 Dataset of the other fault

The dataset gathered from the arc model to represent the other faults that can occur in the PV system such as the fault of the short circuit. These records are generated to enhance the performance of the detection method through the ability of discrimination between these types of fault and the series arc as shown in figure (6).

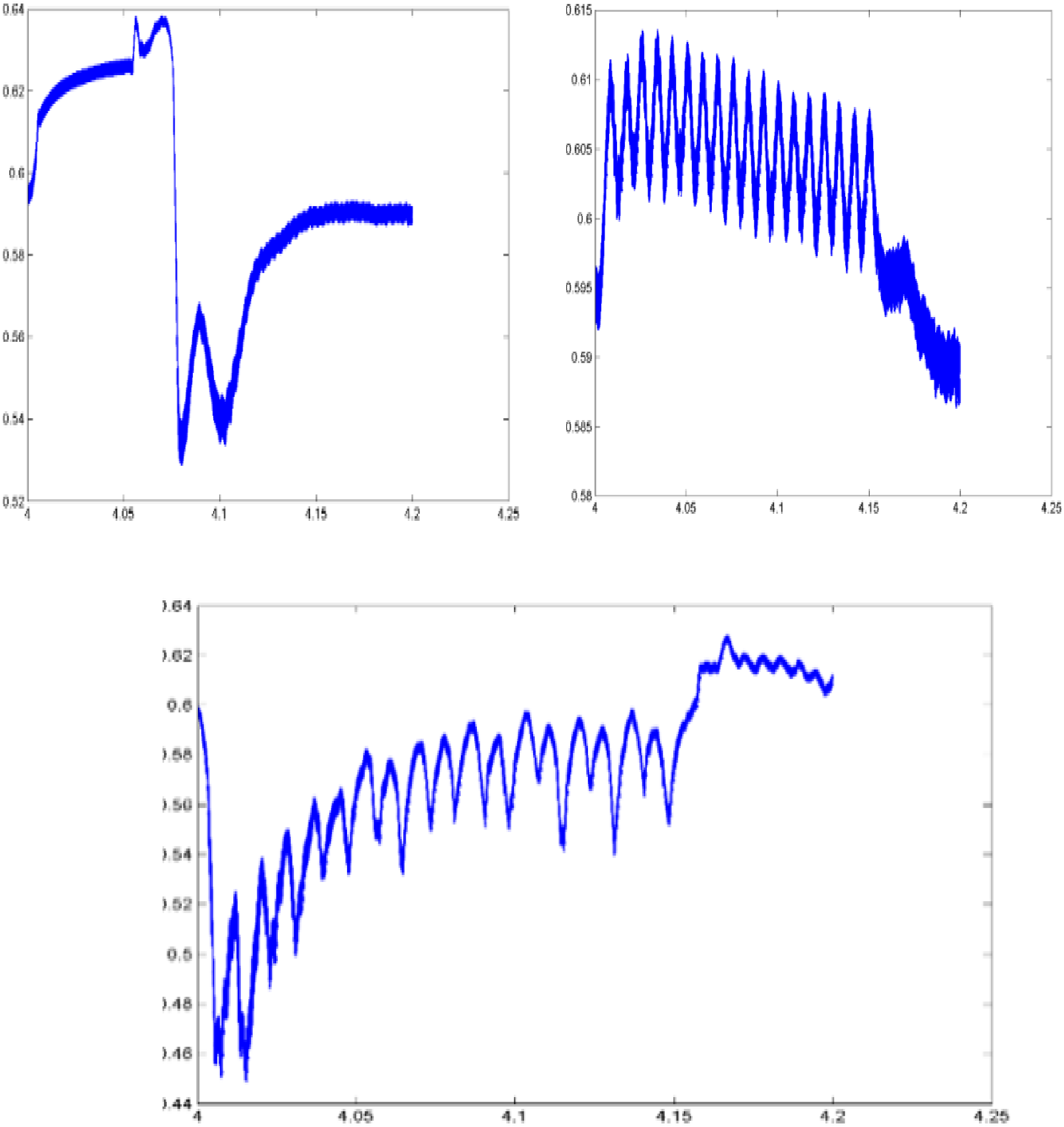


Figure 6. Different samples of faults

3.1.3 Series arc fault

This dataset represents the series arc fault as shown in figure (7). It was generated from the used circuit of the arc fault model. However, in reality, several reasons lead to the occurrence of this type of faults such as the incorrect installation, irregular maintenance, and some environmental effects. The proposed method was trained to precisely detect it.

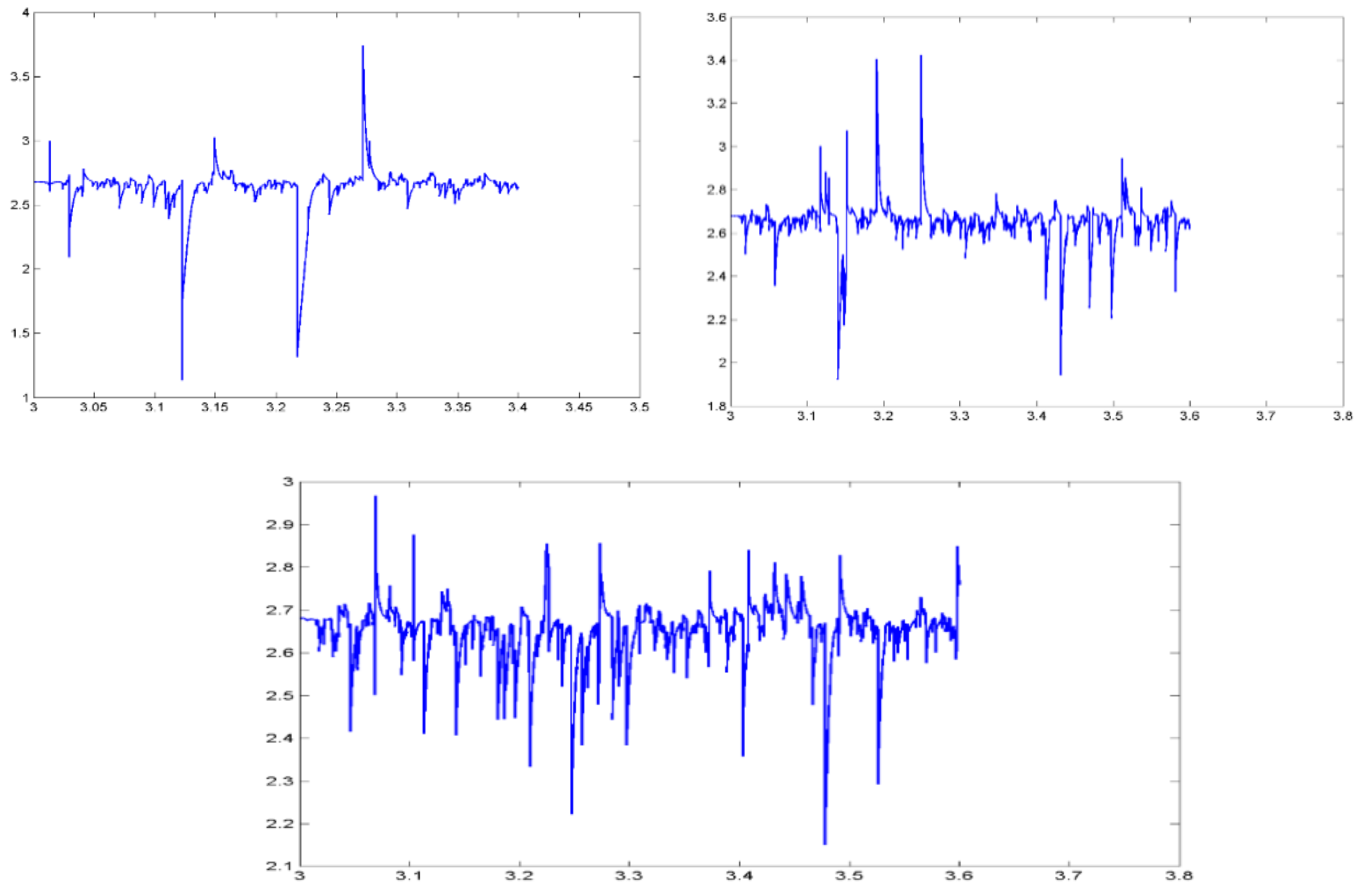


Figure 7. Several samples of the series arcs records

3.2. The suggested schema

The Architecture of the suggested schema is shown in figure (8). It can detect the series arc fault and classify the other issues that may happen in the PV system. It has two main characteristics which are illustrated as follows:

1. The extraction of features which is consists of three convolutional layers that are connected to three layers of max pooling, where input image total volume is and feature map total volume
2. The procedure of the classification is consisting of neurons of fully connected layers.

Furthermore, ReLU and Softmax are selected and used as an activation function in the hidden and output layers, respectively. Also, Dropout with different values is used to eliminate the occurrences of the over-fitting problem, the details of the model are shown in table (2). However, depending on the number of neurons and hidden layers the model performances are changed.

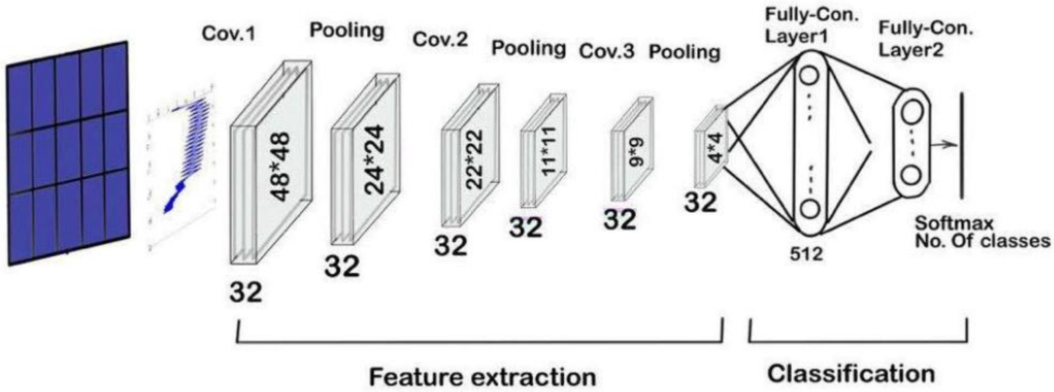


Figure 8. The architecture of the detection and classification schema

The accuracy of the detection method was evaluated with test data and its performance was comparatively calculated.

Table 2. Suggested schema model

Layer Type	Activation	No. of Kernel	Dropout	Patch_Norm.	Kernel Size	Stride	Output
Conv. 1	Leaky Relu	32	0.2	-1	3 × 3	1	48 × 48 × 32
Maxpooling	-	-	No	-	2 × 2	2	24 × 24 × 32
Conv. 2	Leaky Relu	32	0.2	-1	3 × 3	1	22 × 22 × 32
Maxpooling	-	-	No	-	2 × 2	2	11 × 11 × 32
Conv. 3	Leaky Relu	32	0.2	-1	3 × 3	1	9 × 9 × 32
Maxpooling	-	-	No	-	2 × 2	2	4× 4 × 32
Linear	Leaky Relu	1	0.5	-1	512	-	512
Linear	Softmax	1	No	-	No. of classes	-	No. of classes

3.3. The performance and evaluation

Python used to simulate the suggested schema where Keras_Tensorflow_Google was used. The performance of the schema was evaluated in term of accuracy metric and loss metric as follows:
The Accuracy Metric which is an indicator of the ratio of the correct classification; the suggested schema achieved a high accuracy of 98.9% (0.989) as shown in figure (9).

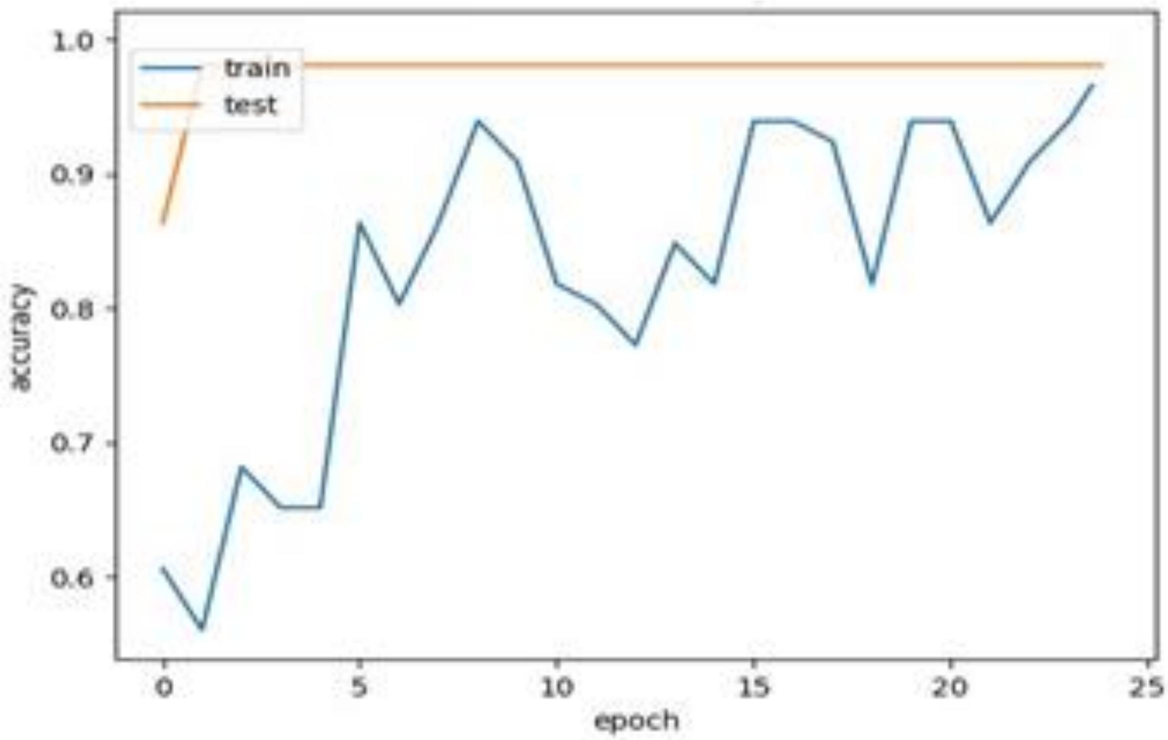


Figure 9. Model accuracy

Loss Metric is an indicator that represents the opposite case of the accuracy metric. It refers to the ratio of cases that classified incorrectly, the model loss of the suggested schema was approximate to 1.1% (0.011). As shown in figure (10).

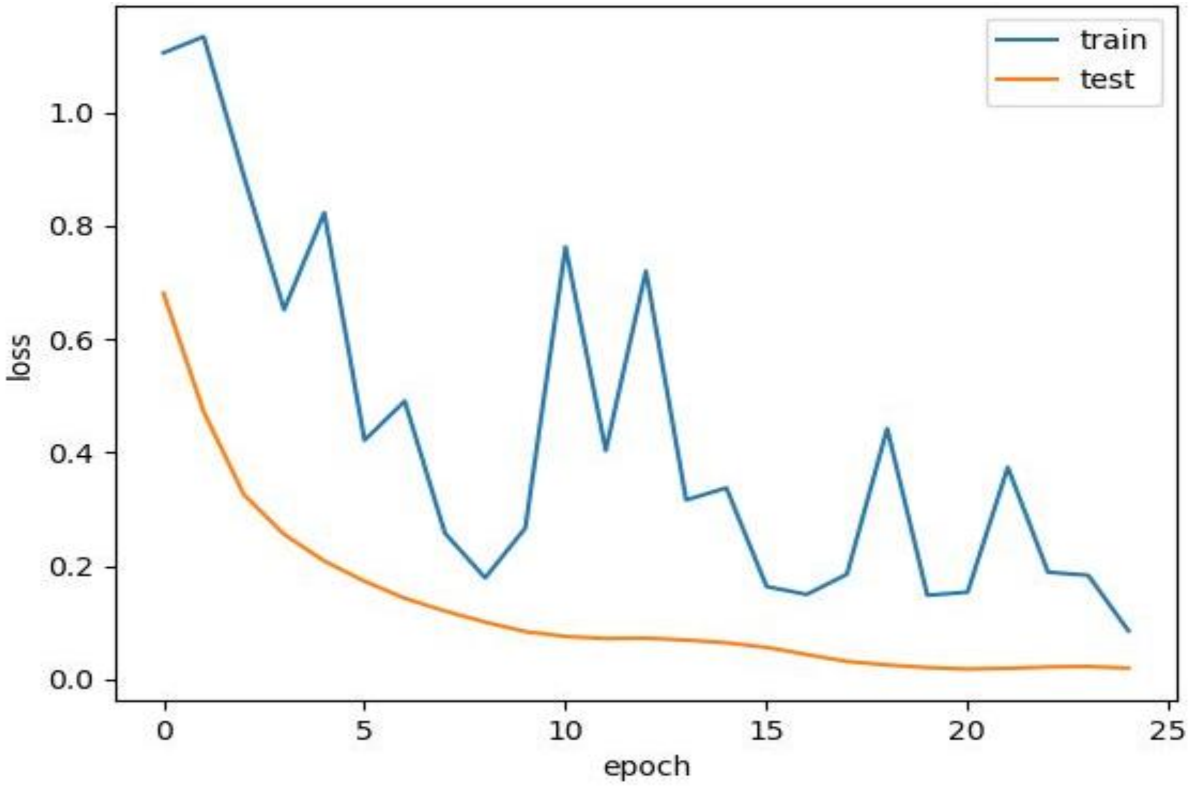


Figure 10. Model loss of the suggested schema

The suggested schema was compared with other prior methods that based artificial intelligence methodology in terms of the overall accuracy of the method, the classification ability of the normal and other fault cases to accurately discriminate the series arc fault. Furthermore, reliability which is considered as an important criterion that some of the methods are heuristic that leads to making their reliability difficult to be proved. The other criteria that should be also taken into consideration are the over-fitting problem that leads to a degradation in the performance of the system. Also, the complexity of computation acts as an important role that many probabilistic model-based such as HMM need additional effort [27]. Table (3) summarized the comparison with other methods based on these criteria.

Table **3**. A comparison with prior methods

System	Methodology	Accuracy	Fault Classification	Reliability	Over-fitting Solution	Computational Complexity /Effort
James et al. [31]	ANN	73%	×	×	×	Medium / high
Zhan et al. [32]	SVM	99%	×	×	√	Medium / high
Benjamin et. al [33]	Fuzzy	95.8 %	√	×	×	Low / Medium
Rory et. al [34]	HMM	98.3%	√	×	×	High
Shibo et. al [35]	CNN-GAN	98.5	×	×	×	Very High
The Proposed Method	CNN	98.9%	√	√	√	Low

It can be seen obviously that the proposed method achieved a high accuracy of 98.9 % with the ability of classification of the series arc fault, it is trained to discriminate the normal cases (inverter startup, load change) and other faults from the series arc fault. Moreover, it was a reliable method and eliminate the over-fitting that happen through the using of appropriate Dropout values; also, the proposed method was simulated with less effort and no need to incorporate it with an additional technique.

4. Conclusion

To accurately identify the problem of the series arc fault and state the factors that lead to creating this fault, an arc fault model based on the hyperbolic model has been chosen and simulated using PSCAD software to collect the necessary records. Then these records are classified to cover all the issues that occur with the PV system. After completing the process of collection and classification of the generated records, the suggested Schema-based CNN is proposed and trained using Python to precisely detect the series arc fault. In more detail, a large number of signals will be generated when the series arc fault occurs, where these signals are high frequency. The simulation results show that the proposed method can detect these signals with good and high accuracy reached 98.9%. For future work, the proposed method planned to be implemented based on Raspberry.

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