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Original Article

Arc Fault Detection and Classification in DC Microgrid Using Deep Neural Network

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Abstract - *High resistance DC arc faults in the DC microgrid can create serious damage to the microgrid and put the operator's safety in danger. If it is not quickly found and eliminated. Available pattern-based fault identification approaches do not perform as expected due to the nonperiodic nature of arc fault and the presence of multiple switching converters. This research suggests using Wavelet Transform (WT) in conjunction with deep neural networks to detect arc faults in DC microgrids. Multi-Layer Perceptron (MLP)/Dense neural networks and Convolution Neural Networks (CNN) have been employed in this proposed methodology. The MATLAB simulation using the Cassie arc model is developed, and simulation results. According to the simulation results, MLP and CNN have respective arc fault detection accuracies of 95.5% and 96.4%. The result also shows that CNN performs better in various degrees of noisy signal conditions.*

Keywords - *Deep neural networks, Fully connected networks, Multi-Layer Perceptron, Convolutional Neural Networks.*

1. Introduction

The DC microgrid with incorporated solar generation is the most simple, stable, cost-effective, adaptable, and profoundly effective answer to individuals living without admittance to power [1-2]. Two criteria can be used to categorise DC microgrid faults involving short circuits and arcs. A DC arc fault results in a DC microgrid because of insulation degradation in the electrical conductor and high DC voltage. Such a fault, if it goes undetected and is not extinguished can cause damage to the entire system and cause fires. Unsafe arc faults can occur as series or parallel arcs [3].

When the conductor is connected in series with the load breaks, a series arc may form. Series arcs usually do not produce enough heat energy to start a fire. The parallel arc fault, which can appear as a ground fault or a short circuit, is more hazardous. The probability of a fire and the exponential growth in thermal energy are caused by the high fault current in a parallel arc fault. The system impedance and the arc fault's own impedance both restrict the amount of current that can flow in a short circuit, parallel arc fault. [4]. In contrast to an AC system, where power electronics are usually only present at the point-of-load, a DC system necessitates the installation of DC/DC converters in the distribution system. These converters provide dispersed capacitance to the system, creating many pathways for high-frequency signals to couple. The arc signature may be obscured by high-frequency noise from the DC/DC converter switching and other electromagnetic interference, enabling an arc to form and persist undetected [5]. Extremely less exploration is devoted to acknowledging DC arcs when contrasted with AC arc detection. The fact that arcs in DC systems are not periodic due to which pattern recognition-based detection methods may not be able to identify their amplitude or frequency tracks which poses a major challenge to their detection [6].

Snehamoy Dhar et al. have presented a new differential current-based quick fault detection and location scheme for multiple photovoltaic-based DC microgrids [7]. However, this method does not consider the effect of switching noise signals. Suyong Chae et al. proposed a series DC arc fault detection algorithm using relative magnitude comparison [8]. DC microgrids with several switching devices are unsuitable for this technique. Wavelet-based arc fault detection is proposed by Wang et al. [9]. Time-frequency domain information gives better results compared to Discrete Fourier Transform (DFT). However, it fails to provide information regarding the type of arc fault and its location. Miao Li et al. presented a FET-based hybrid method to detect series arc faults. When an arc fault occurs, the current change is detected using the window-by-window detection approach. Hence, the correctness of the arc fault recognition is directly proportional to the selection of window size [10]. Dual state-parameter estimation-based series arc fault detection required a serious level of accuracy for parameter estimation [11]. Hence it is important to propose an arc fault detection method that could accurately detect the type of the arc fault and its location much before creating damage to the system. In order to identify DC arc faults, this research suggests a fault recognition and classification technique based on Deep Neural Networks (DNNs). Any kind of data can be processed using the DNN method, primarily CNN, which can extract features on its own. The suggested fault detection method's performance is independent of the location of the defect and the rate of signal deterioration. There are six sections in the paper. Section 1 comprises a brief introduction to arc faults in DC microgrids and their complexity. Section 2 explains the proposed methodology of DC arc fault detection. Section 3 comprises the MATLAB simulation model to test the proposed DC arc fault detection scheme and its results, followed by a conclusion in Section 4.

2. Methodology

Figure 1 shows the methodology of arc fault detection in the form of a flow chart. In this research, we propose and implement Machine Learning (ML) based methods for arc fault detection and classification in DC distribution systems. Compared to conventional computational algorithms, the machine learning-adapted methodology has a higher computational accuracy. The features involved in developing machine learning for fault detection and classification are the fundamental frequency, fault voltage, and current components at fault circumstances.

High-frequency transient signals can be seen in the voltage and current waveforms during failures. To extract the necessary information, transitory signals are broken down using the Wavelet Decomposition (WD) approach. The fault information extracted from wavelet transform is used to train classifiers Convolutional Neural Networks (CNNs) and Multi-Layer Perceptron (MLP). Using a confusion matrix, the created algorithm's performance is evaluated, and the outcomes show remarkably high accuracy.

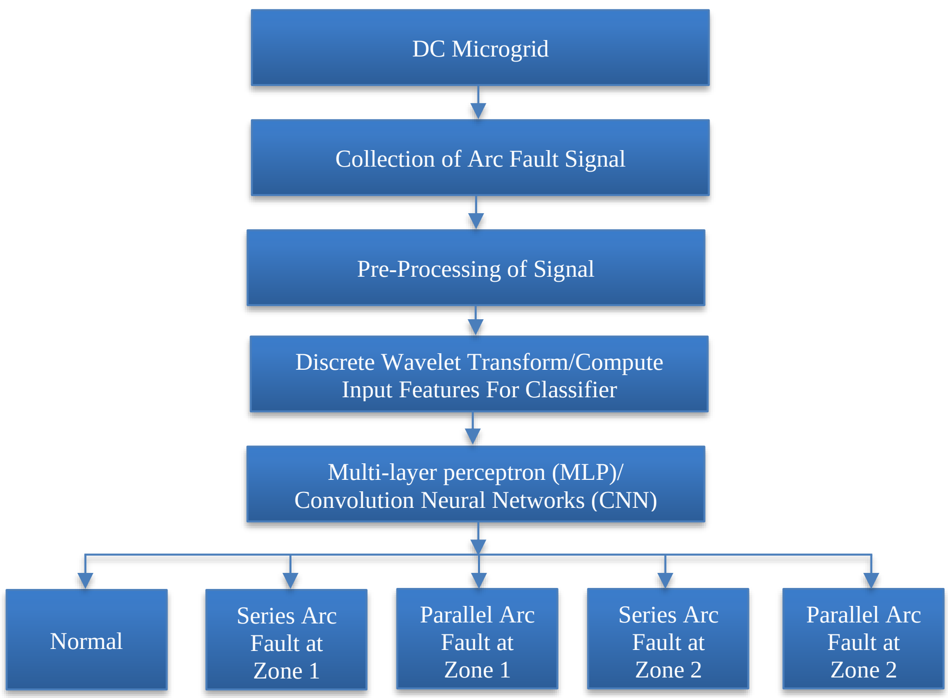

Fig. 1 Methodology of DC arc fault detection

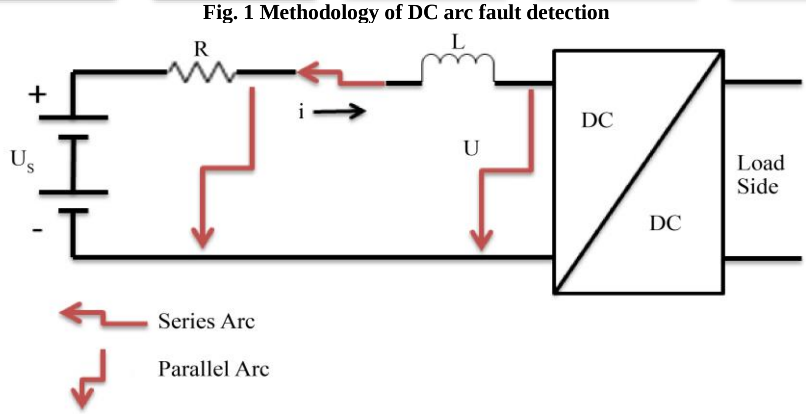

Fig. 2 DC arc fault equivalent circuit

2.1. Types of Arc Fault Data Set

In order to analyse the features of the arc fault, Figure 2 depicts an analogous circuit for DC series and parallel arc faults. The analogous circuit consists of loads, an arc fault production unit, and a DC/DC converter. DC arc faults can be produced in series or parallel by the arc fault generation unit.

This research uses the Cassie arc model to explain how an arc defect starts in a DC microgrid circuit [12]. The way the arc interacts with the electrical circuit during a fault is known as the Cassie arc. The following differential equation uses the Cassie arc model to represent the dynamic properties of a DC arc.

$$\frac{1}{g}\frac{dg}{dt} = \frac{d\ln g}{dt} = \frac{1}{\tau}\left(\frac{u^2}{Uc^2} - 1\right) \tag{1}$$

Where,
g the arc's conductance,
u Voltage in the arc,
I Flow of current via the arc,
Uc Constant arc voltage,
τ Arc time constant.

The above equation states that the nature of the arc fault signal depends on arc resistance. Arc resistance is the function of arc gap length. An arc fault also depends on source voltage as well as changes in load conditions [13]. The DC microgrid is split into two zones for the study. Five situations are used to capture the data: normal, parallel arc fault in zone 1, parallel arc fault in zone 2, series arc fault in zone 1, and series arc fault in zone 2. The simulation time is fixed as 2s for a 20 kHz sampling frequency.

2.2. Data Preprocessing

The arc fault data collected from the simulation model is augmented by adding noise signals. This additional noise signal represents the practical signal that results due to the presence of electromagnetic interference noise and measuring instruments [14]. Zero mean Gaussian distribution random noise is added to generate 10 different faults from one measurement. This facilitates an increment in the data set by 10 times. Further expansion of the data set is done by applying 2nd and 3rd order smoothing and sharpening fault signals. Therefore, for training purposes, 10 times (after adding random noise and smoothing and sharpening) of actual data is available [15].

2.3. Discrete Wavelet Transform

A Discrete Wavelet Transform (DWT) is a method that breaks down a given sign into low-frequency and high-frequency components [16]. This work uses the dyadic-orthonormal wavelet transform using Daubechies 3 (db3) to identify the features of arc faults. The arc fault signal is measured at each zone, and wavelet coefficients are calculated using DWT. The system's fault status is indicated by a change in energy at one or more frequency bands. This decomposed energy signal is utilized to train the respective classifier.

2.4. Deep Neural Network

In Artificial Intelligence (AI), deep learning is a subfield of machine learning. DNN is predominantly utilized for classification and pattern recognition [17]. Out of the different architectures of DNN, the most widely used varieties are Convolutional Neural Networks (CNNs) and Multi-Layer Perceptron (MLP), sometimes referred to as dense neural networks.

2.4.1. Multi-Layer Perceptron/Dense Neural Network

Multilayer Perception is the most popular Machine learning algorithm. In a multilayer perceptron, every node in the current layer is linked to every node in its preceding layer's output [18]. The classifier is the final layer, and the number of neurons in the output layer corresponds to the number of classifications in the dataset.

2.4.2. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are Deep Learning algorithms that possess the ability to receive an input signal, allocate significant learnable weights and biases to different signal features, and distinguish between them [19]. A CNN is a neural organization including a feed-forward structure that contains three sorts of layers: Convolutional Layer (CL), the Sub-inspecting Layer (SL), and the Fully-connected Layer (FL). The FL layer is the final layer of a dense network where the types of faults and the number of outputs are equal.

3. Results and Discussion

3.1. Dataset Collection and Pre-processing

MATLAB/Simulink is used to model the DC arc fault detection circuit, as seen in Figure 3 [20]. Two km is the length of the DC line. Zone 1 is the area up to one kilometre of the DC line from the source, and Zone 2 is the remaining distance. The Cassie arc model is placed at zone 1 and zone 2 in series and parallel to simulate series and parallel arc faults [20]. The resistive DC load is connected at the end of the system. The input to the DC bus is 100V DC. AC component with frequencies of 2000 Hz represents power electronic switching noise, and 120 Hz frequency components represent power ripple are added to create realistic readings. Table 1 displays the remaining simulation parameters.

The system is marked as normal once it is simulated under typical circumstances. The following time intervals are used to gather data for the fault conditions: 0-0.5 s, 0-1 s, and 0-2 s. The fault conditions are:

- Zone 1 series arc fault
- Zone 1 parallel arc fault
- Zone 2 series arc fault
- Zone 2 parallel arc fault

Each type of fault is simulated 1000 times by varying the arc time constant τ, constant arc voltage Uc and loading conditions. All these types of fault signals are undergone pre-processing. The signal pre-processing is done by data augmentation by adding zero-mean Gaussian distribution random noise and applying 2nd and 3rd order smoothing and sharpening. The total data set includes 13 cases, split into one normal case and 12 fault cases collected from 4 arc faults at 3 different time intervals. Total data obtained is 13X1000 = 13,000. These data sets are then undergoing augmentation, and the size of the data set is increased to 13,000X10X4 =5, 20,000.

Figure 4's waveforms display the load voltage at zone 1, arc voltage, bus voltage, and AC harmonic voltage with arc time constant τ = 0.0008, Uc = 500 V. Similarly, other fault types are simulated and collected in the dataset.

Table 1. Description of simulation parameters

Sr. No	Simulation Block	Parameters Description
1	Voltage of DC source	100 V
2	AC Harmonics 1	Voltage amplitude = 10 V, Phase in degree = 0, Frequency = 2000 Hz, Sample time = 0
3	AC Harmonics 2	Voltage amplitude = 10 V, Phase in degree = 0, Frequency = 120 Hz, Sample time = 0
4	Cassie arc model	Time constant τ = 1.2 µsec, Uc = 500V, g(0) = 1000 sec Contact separation starts= 1 ns
5	Load	Active power = 10KW, nominal voltage =1000V.
6	Buffer	64 channels in the output buffer
7	DWT (Dyadic analysis filter bank)	Wavelet order = 3, number of levels = 4, filter (mother wavelet) = Daubechies

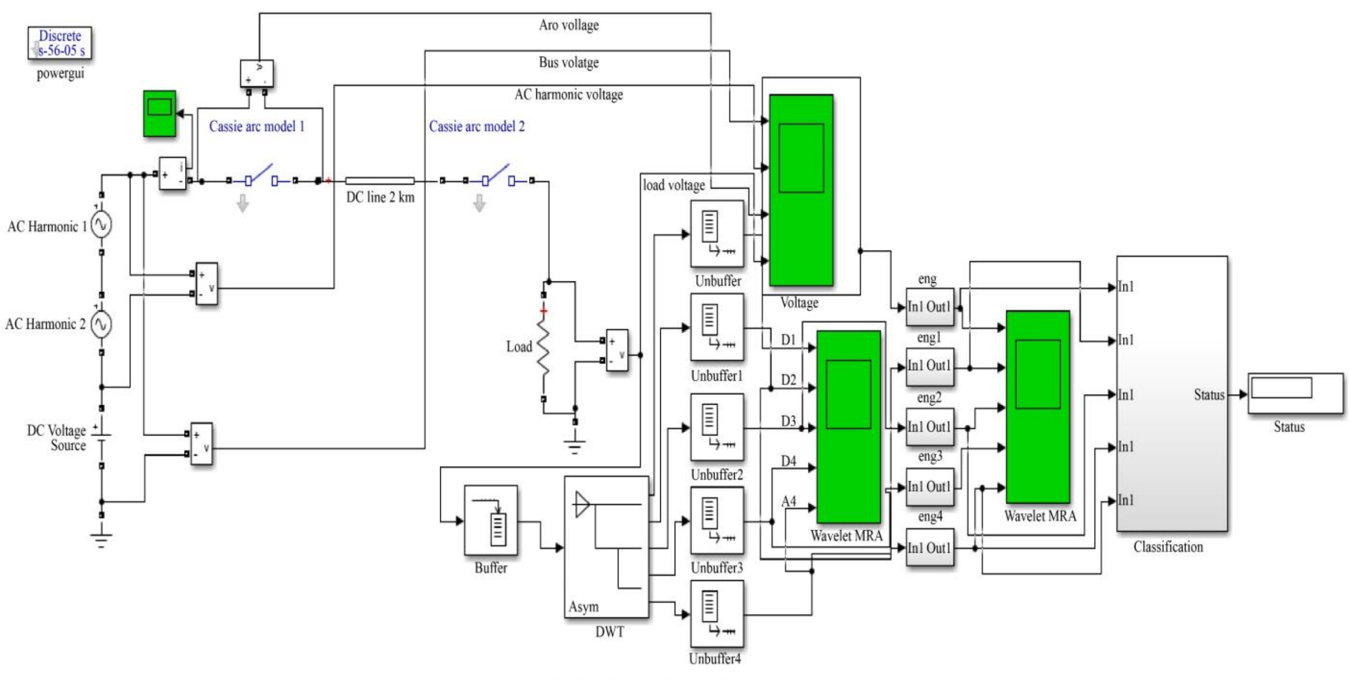

Fig. 3 MATLAB simulation model of proposed arc fault detection

3.2. Computation of Input Features for Classifier Using DWT

The particular and approximate coordinator data are shown in the Figure 5 wavelet multi-resolution analysis window when an arc flash happens in zone 1 of DC line operation. In this instance, zone 1 of the DC wire experiences an arc.

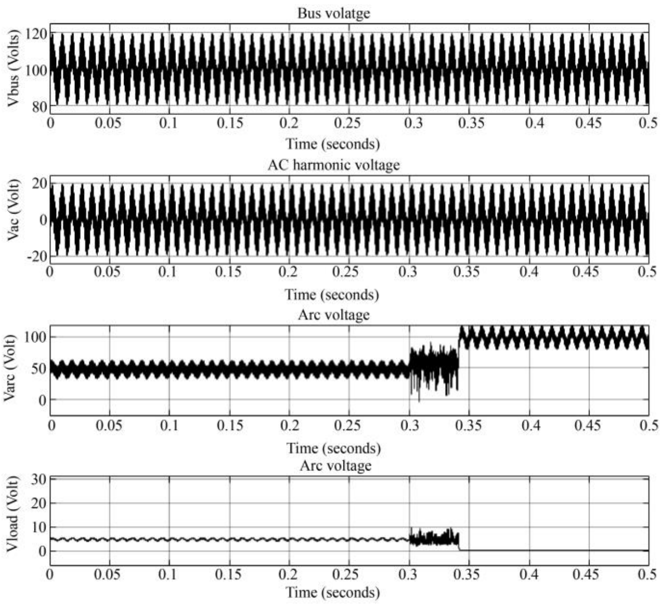

Fig. 4 Arc fault waveform for bus voltage, AC harmonic voltage, arc voltage and load voltage

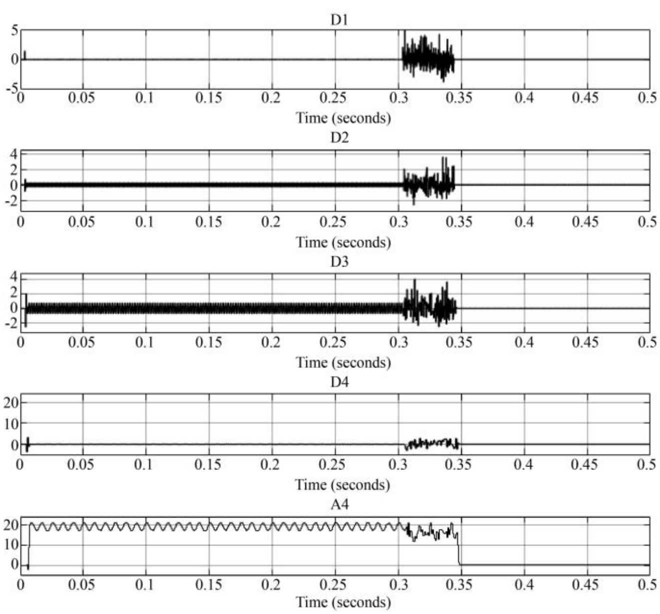

Fig. 5 Wavelet multi-resolution analysis of load voltage during arc fault occurs in zone1 at 0.3 second

As a result, before the arc is started, the detail coordinator data in this case—D1, D2, D3, D4, and Approximation A4—are constant. The arc is started at 0.3 seconds, after which the coordinator data changes. For multi-resolution wavelet transform analysis, the Daubechies mother wavelet is employed.

Figure 6 displays the wavelet spectrum energy at level 4 of the multi-resolution analysis for the approximate signal A4, detail signals D1, D2, D3, and D4. During normal functioning, it is found that the spectral energy of the signals remains constant inside this window.

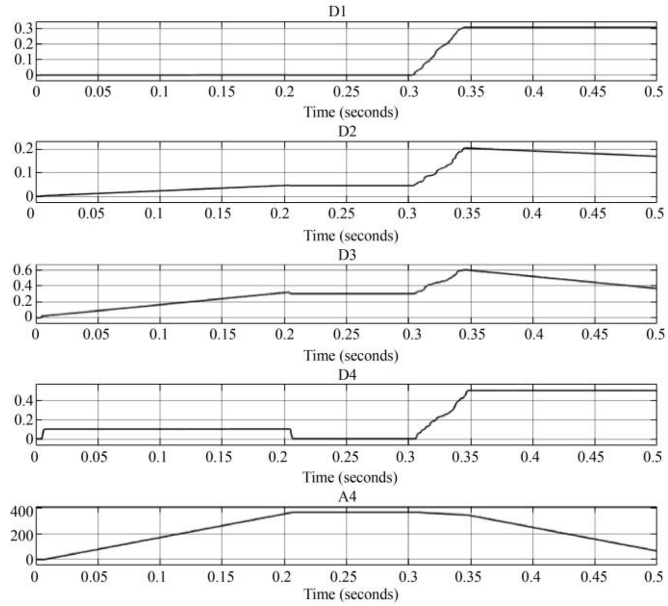

Fig. 6 Localised energy spectral of wavelet coefficient for arc fault occurs in zone 1 at 0.3 second

3.3. Arc Fault Detection Using Proposed Deep Neural Network

The proposed arc fault detection method uses two different networks, MLP and CNN. The TensorFlow framework is utilised to develop both networks. The total dataset is categorized into 70% for training, 20% for validation, and 10% for testing.

The designs of both networks are based on the size of the input signal. Process weights are initialised randomly, and the loss function is defined during training. The method that is being given uses the cross-entropy function as a loss function. By modifying the weight of the neurones and reducing the loss function, a higher precision is attained [21]. The networks are trained with defined fault types and labeled accordingly.

The validation step is initiated at the end of the training. Validation processes verify the accuracy of the trained network and check for errors. The fault detection scheme works in two steps; initially, input signal probabilities that belong to a certain fault type are calculated. This calculated probability is compared with the trained network data set probabilities. Based on the probability match, the fault type and location are identified.

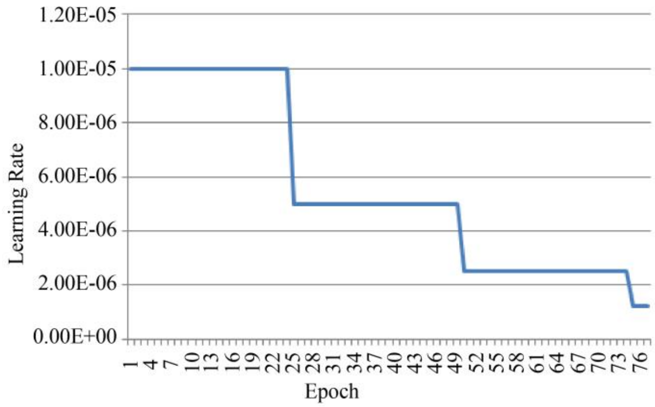

Fig. 7 Learning rate of network Vs epoch

Table 2. Fault detection accuracy in percentage

Fault Type	MLP	CNN
• Normal	100	100
• Zone 1 series arc fault	96	96
• Zone 1 parallel arc fault	93	92
• Zone 2 series arc fault	96	96
• Zone 2 parallel arc fault	95	94

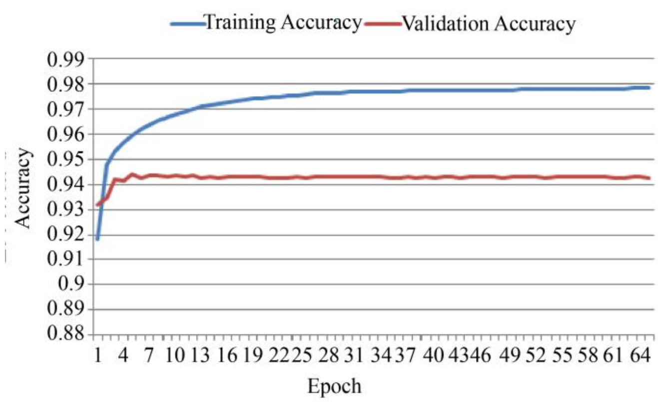

Fig. 8 Training accuracy of fault detection of model

Table 2 displays the classification accuracy of Dense and CNN during arc faults and in healthy conditions. The length of the input signal is equal to the number of neurons in the input layer. A dense network is designed with three hidden layers with several nodes 1500-1000-500 respectively [22]. The number of classes decides the number of nodes in the output layer. In this proposed technique, the number input signal is classified into 5 classes. The activation technique used for hidden layers is ReLu, and the output layer is soft-max. The cross-entropy loss function is used during training, and training is done with Adam optimizer. After every 25 epochs, the learning rate is updated to half for convergence to the global minimum shown in Figure 7.

The input size of CNN is the same as that of the fault signal. There are three convolutional layers, and each layer has 4, 8, or 16 filters, respectively [23]. The input and output layer activation methods, as well as the loss function minimization, are identical to those used in dense neural networks. In order to achieve convergence to the global minimum, the learning rate in this network training is also changed every 25 epochs to half. The average accuracy for all types of fault detection with CNN is shown in Figure 8.

Figure 9 shows the loss with respective epochs for training and validation of CNN. Hard stopping criteria of 100 epochs are used and can also be replaced with the consecutive epoch error difference criteria, wherein the training is stopped if the consecutive epoch error difference is not more than the chosen threshold. The figure shows the accuracy of training and validation over the training epochs, which correlate with the loss curves.

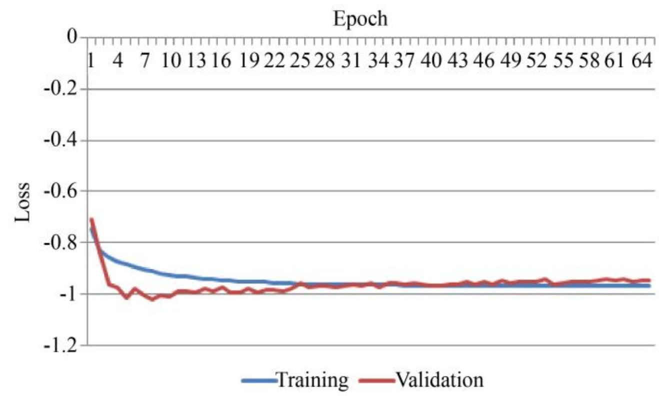

Fig. 9 Loss vs epoch curve of both training/validation of the model

For the single defect, the training time is 40 ms. When the model is being tested, the model file is loaded and trained as an HDF file. To evaluate the complexity of networks, the number of layers varies from 2 to 6 in both Dense and CNN. It is observed that the classification accuracy reaches the maximum value for 3 layers. For further increases in the number of layers, accuracy gets saturated for both networks.

By introducing 10dB of Gaussian random noise into the fault signal, the suggested protection strategy is additionally tested in a noisy setting. This added noise represents the high-frequency noise produced by communication channels and measuring devices used in the DC microgrid [24].

Comparatively, CNN performs well in the presence of noise. The accuracy of both networks is shown in Table 3 in the presence of a noise signal.

Table 3. Fault detection accuracy for noisy signal in percentage

Fault Type	MLP	CNN
• Normal	100	100
• Zone 1 series arc fault	94	95
• Zone 1 parallel arc fault	94	95
• Zone 2 series arc fault	95	96
• Zone 2 parallel arc fault	94	96

The confusion matrix summarizes the performance of the classification algorithm in the form of a table.

A =

100	0	0	0	0
1	95	1	2	1
2	1	95	0	2
1	1	1	96	1
0	1	2	1	96

The overall statistics of the performance of CNN as summarized and shown below.

Accuracy: 0.9640
Error: 0.0360
Sensitivity: 0.9640
Specificity: 0.9910
Precision: 0.9640
FalsePositiveRate: 0.0090
F1_score: 0.9639
MatthewsCorrelationCoefficient: 0.9550
Kappa: 0.8875

Two other available classifiers, the Support Vector Machine (SVM) and the Gaussian Mixture Model (GMM), are also compared with the proposed method. Based on classification accuracy, specificity, and execution time, the performance of the suggested classification technique is compared with that of GMM and SVM. The preprocessed arc fault data set is used to evaluate the effectiveness of SVM and GMM. Figures 10, 11, and 12 show these classifiers' relative performance for the same dataset.

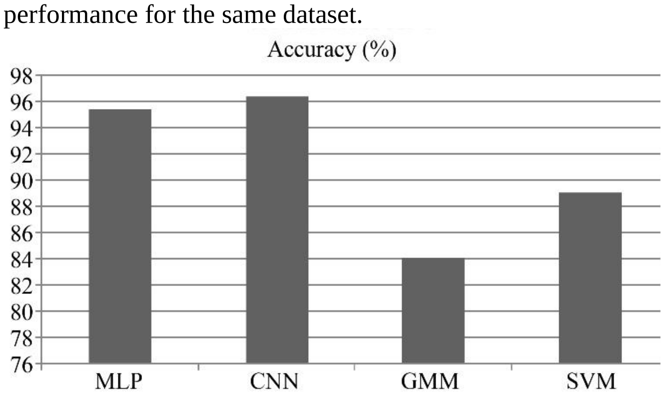

Fig. 10 Accuracy comparison

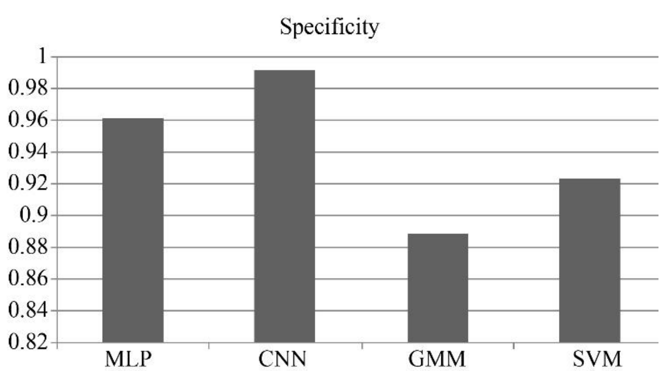

Fig. 11 Specificity comparison

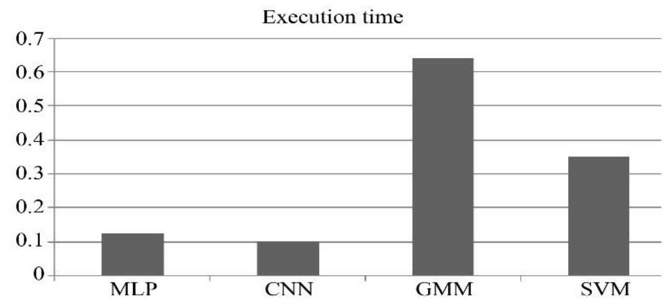

Fig. 12 Execution time comparison

The results demonstrate that, when compared to existing classifiers, the suggested classifiers have higher accuracy, higher specificity, and lower execution times for fault type discrimination. The accuracy achieved for classification using the TensorFlow and the MATLAB MLP and CNN models are 96% and 95.6%, respectively, as shown in Table 2. The CNN shows an improved detection accuracy of 96.4 % in the presence of noise, as shown in Table 3. The confusion matrix and overall statistic performance also show the exceptional performance of CNN in arc fault detection. The proposed method's performance is compared with GMM and SVM classifiers. The result shows that the accuracy achieved by MLP and CNN is 95.4% and 96.4%, respectively, Whereas GMM gives 84% and SVM 89%. The specificity of the proposed MLP and CNN are 0.961 and 0.991 compared to GMM and SVM, which give 0.889 and 0.923, respectively. The execution times required by proposed classifiers are comparatively much less than GMM and SVM. The proposed algorithm is also tested with experimental results demonstrating an accuracy of 96% for MLP and 98% for CNN. Thus, we can conclude that the proposed methodology of the DNN classifier proved an efficient method for DC arc fault detection.

4. Conclusion

In this paper, the application of deep neural networks for DC microgrid arc fault diagnosis is demonstrated. Arc failures are simulated, and a DC microgrid serving DC load is modelled in MATLAB. The input for the neural networks is the arc failure signal that was acquired from the simulation. The defect feature is extracted using the discrete wavelet transform, which also serves as the neural network's input. This work has emphasised how important it is to choose the best DNN setup in order to maximise network performance. It has been noted that the CNN performs better than the Dense network when there is noise (96.4%), but the Dense network performs better when there is no noise (96%). The performance of the proposed method is also verified in terms of accuracy, specificity, and execution time result shows 96.4% accuracy, 0.991 specificity, and 0.1 execution rate comparatively existing classifiers. Therefore, based on the data, we can say that the suggested deep neural network models outperform other classifier models in the given situation.

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