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Monitoring and optimizing the state of pollution of high voltage insulators using wireless sensor network based convolutional neural network

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ABSTRACT

In this paper, a wireless sensor network (WSN) is combined with Convolutional Neural Network (CNN) forming a hybrid framework to detect the pollution state in high voltage insulators. The WSN is formed by the collection of sensor readings from each high voltage insulator over the transmission tower. The collected sensor readings from the sensor network is sent to the processing unit or detection unit, where CNN is used for the purpose of detecting the partial discharged high voltage insulator. The CNN is used with partial discharge diagnosis model to detect the dischargers in high voltage insulators. The extraction of relevant features from the CNN helps to improve the detection. The experimental validation are conducted on the proposed model with collected training datasets and real time testing datasets. The proposed method is compared with existing models to test the partial discharges in high voltage insulators, namely Artificial Neural Network, Fuzzy and Ant Colony Optimization. The result shows that the proposed method is effective in detecting the partial discharges than the existing methods in terms of False Acceptance Rate and Missing Detection Rate.

1. Introduction

Erosive discharges, which can cause the failure of HV components such as cables, capacitors and inlet coils, also are referred to as Partial Discharge (PD) in high voltage technology. In the power industry, partial discharge appearing both inside and outside isolating materials is a persistent issue. In faults such as cavities inside an insulation material, an inner partial discharge is initiated while an external partial discharge at the metal insulator interface occurs. Both types of PD i.e. external and internal are of the same type. The town send electron avalanches can develop into micro- sparks and streamers [2].

One of the main reasons for the isolation reduction between ground and phase in high voltage transmission lines is the pollutants accumulation on the HV insulator surface. The pollutants under high humidity form a conducting layer on the surface of the isolator. The non-uniform flow of leakage current forms dry bands in the conductive layer that concentrates on the electric field, which leads to partial discharges at these conductive layer. Partial discharge phenomena can increase their intensity and rate up to the full discharge of a flashover from line to ground.

One of the most important problems for power transmission is the pollution flashover observed with insulators that are used in high voltage transmission. The problem is very complex because of several aspects such as modeling difficulties with complex isolator shapes, different pollution densities across regions. The uniform distribution of pollution to the surface of the isolator and unknown effects on pollution from humidity [3].

One of the guiding factors in the dimensioning and design of insulation on transmission lines is the performance of flashovers in polluted conditions. Therefore, flashover on the polluted insulator is a major problem that power engineers need to resolve [3].

The current leakage signal has sinusoidal waveform, which is superimposed on the partial discharges with intermittent and short pulses. From previous experiments, the speed, amplitude and duration of the sinusoidal pulses are directly linked to the insulator string pollution. It has been found that the classification of rate and amplitude of short pulses superposed on the current leaking waveform is considered as a means to deduce the status of insulator pollution [4].Some static and dynamic modeling were developed in the literature [5-20] to predict the splashing voltage of polluted isolators by making certain assumptions or omissions. However, there exist very few machine learning or artificial intelligence algorithms like artificial neural

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network (ANN), Ant Colony Optimization (ACO) and fuzzy systems to predict or classify the discharges, which is likely to occur.

The proposed idea is inspired from Fontana, E., et al. (2012), where sensor system network is utilized to monitor the state of pollution remotely on HV insulators through satellites. However, the process is takes enormous amount of resources to establish link with satellites and back to the ground unit for processing. Hence, to reduce the usage of resources and to improve the process of monitoring the state of pollution in high voltage insulators, the present study uses the concept of machine learning to detect the presence discharges or state of pollution caused by high voltage insulators. To have an effective utilization of resources and to improve the monitoring and processing ability, the proposed system integrates the wireless sensor system in the tower [1] and the concept of deep learning to monitor and detect the state of pollution in high voltage insulators, respectively.

The outline of the paper is presented as follows: Section 2 discusses the framework for monitoring and detection of partial discharges or the state of pollution. Section 3 discusses the concept of deep learning i.e. Conventional Neural Network (CNN) to detect the state of pollution. Section 4 provides the validation of the proposed work. Section 5 concludes the paper.

2. Proposed method

The proposed method uses wireless sensors system to collect the real-time data of partial discharge from the HV insulator surface where the architecture of which is given in Fig. 1. Further, it uses temperature and humidity sensors to collect the environmental temperature and humidity, respectively.

2.1. Monitoring unit

The optical sensor unit consists of an 840-nm light-emitting diode (LED) connected with a pigtail configuration terminated in a ferrule-type fiber-optic connector. A direct current of 300 mA with pulsed current amplitude of 1A is supported by the optical sensor. This is connected in parallel with HV insulator, which lies at closest distance to the ground terminal and it helps in shunting the leakage current through it. The shunting of leakage current is carried out by grounding the LED cathode with tower and anode with second insulator cap. Thus the positive excursions are recorded by the system [1].

The collected signal from LED sensor, temperature, lightning and humidity sensor is sent to processing module that has the ability of detecting the partial discharge in HV insulators. In existing system, a PIN photo detector is used for detection with four operational amplifier with individual adjustable gain. However, the complications associated with circuitry is avoided in the proposed method. The proposed detection module has a Convolutional Neural Networks (CNN) that extracts the relevant features required to detect the presence of partial discharge in HV insulators. The CNN detects the PD by setting the inputs at the training stage. These inputs at training stage consist of both partial discharge and non-partial discharge high voltage insulators inputs. The CNN is allowed to train using these inputs and finally, testing is carried out to detect the partial discharge in real time environment.

2.2. Convolutional neural network

As illustrated in Fig. 2, CNN unit consists of two parts. One of them is responsible for extracting features and includes the input layer, convolution layers and pooling layers. Feature extractors are convolutional and pooling layers stacked in the network by layers. The second part performs classification using fully connected hidden layers and an output layer. The functions obtained by the last pooling layer as input and classification tasks in this part are fully connected layers.

The input layer receives data to be classified and the convolutional layer then identifies the local characteristics of the inputs collected from sensor unit and saves them as a map. As shown in Fig. 2, the receptive field establishes a connection between the input layer and the convolutional layer. A square weight matrix whose dimensions are significantly smaller than that of the input is a responsive field. A feature map contains node(s) connected by the receptive field to a particular input area. The receptive field runs along the horizontal and vertical axes across the input zone and performs convergence operation as shown in Eq. (1).

$$y_i = \sigma\left(\sum_{r=1}^{F_r}\sum_{c=1}^{J} W_{rc}X_{(r+iS_r)(c)} + b\right), 0 \le i \le \frac{K = F_r}{S_r} \tag{1}$$

where

y_1 is represented as the output value of feature map node;
H is represented as the vertical dimension or the height of input data,
W is represented as the horizontal dimensions or width of the input data;
F is represented as the width size and height of the receptive field and
S is represented as the stride length or the step size.
$(r+iS)(c+jS)$ is represented as the input data element with coordinate $(r+i\times S,\ c+j\times S)$,
w_{rc} is represented as the weight positioned at (r, c) that relies on the receptive field,
b is represented as the bias, respectively.
σ is represented as the nonlinear activation function that helps in extraction of features from the input data.

The extraction of features are carried out with rectified linear unit (ReLU). All feature map nodes share the same weight in the CNN

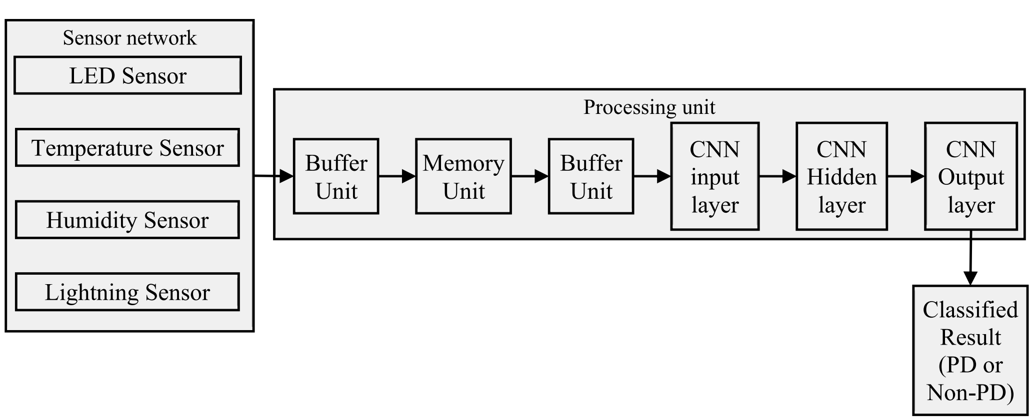


Fig. 1. Proposed Module for Monitoring and Detection.

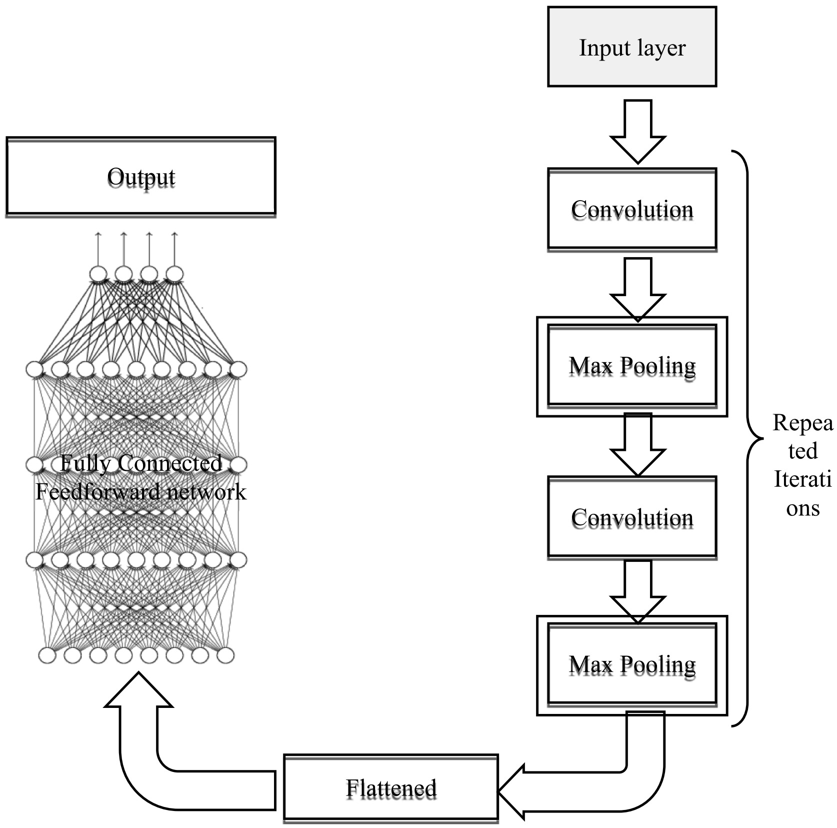


Fig. 2. Convolutional neural network.

architecture. In other words, a single weight matrix is used in the reception field for creating a feature map. It involves attempting to find a similar characteristic feature across the whole input field in the receptive field. In a convolutional layer, several characteristics are generated in general to identify different characteristics by applying the receptive field with different weight matrices iteratively.

In Eq. (1), the computation involves the reduction of input size to in convolutional layer that results in the dimensional reduction as the convolutional layer stack goes deeper. To preserve the result of the processing of the input at the same dimension, a size padding is usually added at both ends and the step length is set to one. The pooling layer generally lies behind the convolutional layer, which reduces the size of the function mapping via the pooling field and at the same time creates a condensed characteristic map by selecting location invariant characteristics. The map size is reduced using max-pooling.

The information of the condensed feature maps in the last pooling layer is transferred to the classification part [21-23]. In this part, the nodes of the first hidden MLP layer are connected to each of the nodes constituting the condensed feature map.

Finally, the output layer, which comprises the same number of nodes as classes, generates the probability score of each class. The model performs the classification to a higher class score in particular. In the classification part can also be used to improve the model's generalization performance. At every workout the dropout skips the update on the weight of certain hidden nodes. It is known to be effective in preventing networks from overpowering data training.

2.3. Diagnosis of partial discharge using CNN

The receptive field weights and the first convolutional layer feature map can be identified in the CNN using the time and variable information that is essential for detection of partial discharge. During the CNN training stage, weights are updated to minimize the detection error using gradient descending method. The greater the magnitude of a certain weight, larger is the contribution of previous nodes for extracting the classification features. For CNN, the importance of a specific sensor reading variable is represented in every weight column in the receptive field of the first convolutional layer. Hence, the contribution level of variable (CLV) of each sensor variable (*j*) is defined as:

$$CLV(j) = 100\left(d(j) - \sqrt{j}\, med(d)\right)^{+} \tag{2}$$

where,

$$d(j) = \left|w_j' - med(w')\right|$$

$$w_j' = \frac{1}{F_r}\sum_{r=1}^{F_r}\left(w_{rj}\right)^{+}$$

$w_j'$is represented as the mean value of positive weights of a sensor variable j with relevance to j^{th} receptive field

w' is represented as the set of weights that varies between $w_1, w_2, \ldots, w_j d_j$. is represented as the difference between the mean value $w_j'$and median value of w'd is represented as the set of variables $d_1, d_2, \ldots, d_j$.

If the value of d_j is larger than median value of variable j, a high score is assigned by the measure in Eq. (2) to variable j, which forms an important variable for feature map. It discards the statistical assumption to distribute the mean weights. The total number of variables selected is controlled by $\sqrt{j}$ in Eq. (2) and the increase in the total number of variables is suppressed by the increasing number of sensor variables of high CLVs.

In CNN, if a single sensor variable has a positive contribution level of variables, then a single feature is selected by the receptive filed for detection of partial discharge. If multiple sensor variables have positive contribution level of variables in another receptive field, the receptive field detects the correlation of the variable with positive contribution level of variables as an effective feature of detecting the partial discharge. If negative contribution level of variables is found in entire sensor variables in the receptive field, then it can be considered as a lack of meaningful features with relevance to the receptive field.

The feature map belonging to the first layer of convolution has a processing time of same row size similar to the input data. The feature map node (i) stores the degree of activation (y_i) of the features belonging to the local input through the convolution of receiving field weights with input data. Therefore, the status of connected input data is reflected by each element y_i. Hence, the feature map with minimal detection errors across the processing time shows similar activation function for the label data. To local features of collected sensor pattern is normalized using following function.

$$z(i) = g\left(\frac{y(i) - y_i'}{\sqrt{\mathrm{var}(y_i')}}\right), 1 \leq i \leq \tag{3}$$

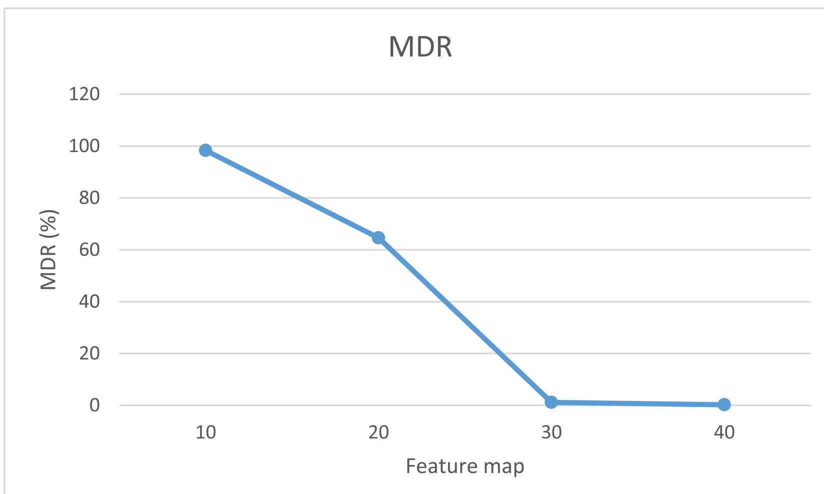
$$g(x, a) = \left\{\frac{\min(x, a)\ if\ x \geq 0}{\min(x, -a)\ if\ x < 0}\right\}$$

where z_i is defined as the i^{th} feature map element of the sensors readings, which are normalized through mean value and variance value for a normal class datasets.

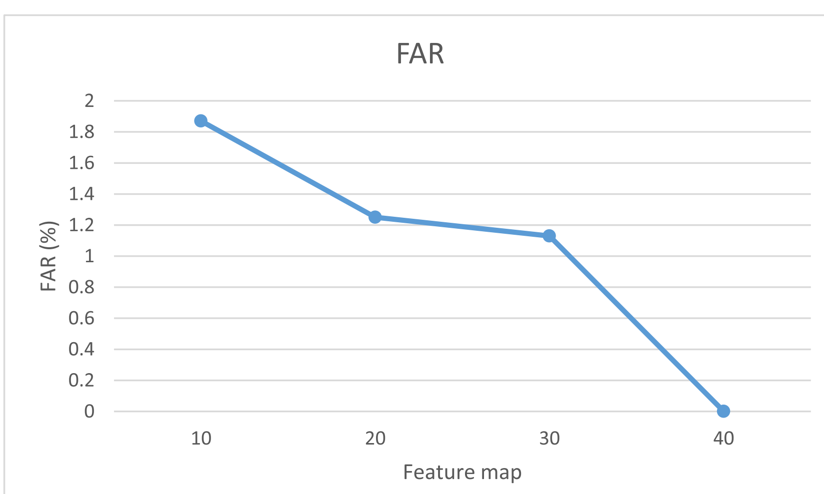
The function map outliers are restricted to the range of the maximum value a to the minimum value -a by function g during the normalization process. The importance of the change in the local function is shown by the value of z at the end of each data collection. A standard feature map with a clear difference between normal and defect classes therefore provides data on the time section of the processing, which displays different models in the raw data. Thus it can be concluded that if the sensor reading shows distortion patterns in a feature map, the changes tends to provide the insights for the disturbance in the process of transmitting the electricity through it.

3. Results and discussions

The data is collected for experimental validation at an interval of 1/10 second from different sensors. The readings of sensor data is scaled between 0 and 1. The collected data is used to train CNN and testing is carried out in real time environment. The training data is carried out with the collected data samples that consists of 5000 normal and 5000 partial discharge samples.



(a)



(b)

Fig. 3. Results of MDR (a) and FAR (b) with 10 feature map.

The performance of the detecting the partial discharges in towers is performed on a computer with Intel Core i7 3.4 GHz and 16 G RAM. An accelerated GPU is used for computing the CNN for detecting the partial discharges in towers and the total training time obtained is ~18 s. Since, there exist very few existing methods to detect the state of pollution via a machine learning framework, the proposed method is tested with those systems namely, ANN, ACO and Fuzzy systems.

Missing detection rates (MDRs) refer to the rate in the monitoring process where an abnormal occurrences were incorrectly identified as normal, but only in the case of fault detection. False alarm rate (FAR) is defined as the monitoring results of normal process of ANN, ACO and Fuzzy systems. The MDR and FAR results are given in Fig. 3 for different conditions 10, 20, 30 and 40 feature map. The CNN with different feature map with layer pair is used for feature extraction. The classifier uses 500 hidden fully connected layers. The first convolutional layer consists of receptive fields of order (3 × 10) and the succeeding layers consists of receptive fields of order (3 × 1) and finally the convolutional layer consists of receptive fields of order (3 × 3). In all models, the stride length is chosen to be unity. The pooling layer uses max-pooling with the size (2 × 1). Finally, the proposed system uses Hotelling statistics (T^2) squared prediction error (SPE) statistics for the detection of PD by CNN. The results of which are given in Fig. 3.

The result shows that the proposed method has lesser MDR and FAR than the existing methods (Fig. 4). The use of 40 feature maps in the proposed system ensures that it performs effective than other methods. This shows that the proposed method effectively detects the partial discharges than the existing methods.

4. Conclusions

In this paper, a hybrid framework is designed that consists of a wireless sensor network and a CNN model to monitor and detect the state of pollution in HV insulators. The wireless sensor network module with temperature and humidity sensor collects well the data from transmission tower and sends it to the distributed processing unit. The processing unit with CNN finds the presence of partial discharge or its state of pollution in HV Insulators by the extraction of relevant features collected by the sensor unit. The comparison with existing methods to detect the fault shows that CNN detects well the state of pollution in HV insulators than other methods. Thus the study proves to be effective, since it utilizes very minimal resources to detect the state of pollution in HV Insulators. However, the study is limited to a smaller region of

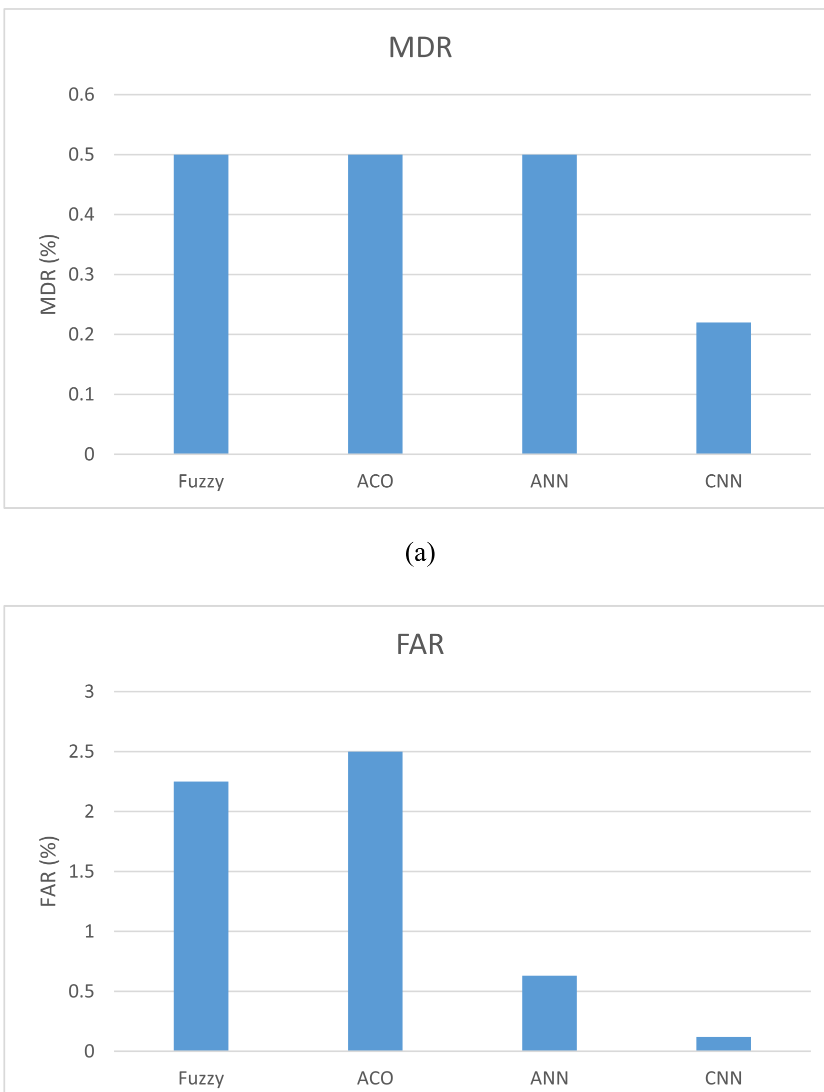


Fig. 4. Results of MDR (a) and FAR (b) with existing method (proposed method uses 40 feature map).

interest. In future the size of the area will be increased to check the effectiveness of the system against big data problem and to check its computational efficiency against this constraint.

Declaration of Competing Interest

Thus the study proves to be effective, since it utilizes very minimal resources to detect the state of pollution in HV Insulators. However, the study is limited to a smaller region of interest. In future the size of the area will be increased to check the effectiveness of the system against big data problem and to check its computational efficiency against this constraint.

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