



Transfer learning for SLG Fault Detection in Ring Distribution System

GARIMA TIWARI
Research Scholar

Department of Electrical Engineering
Deenbandhu Chhotu Ram University of Science &
Technology, Murthal, Sonipat, Haryana, India
18001902001garima@dcrustm.org

Dr. SANJU SAINI
Associate Professor

Department of Electrical Engineering
Deenbandhu Chhotu Ram University of Science &
Technology, Murthal, Sonipat, Haryana, India
sanjusaini.ee@dcrustm.org

1663

Abstract—Extraction of features for any faulty signals is very difficult and critical in any type of fault detection technique. A recent & effective way for feature extraction is a Convolution Neural Network (CNN). This paper firstly collects the data for a faulty line as positive sequences of fault currents then creates scalograms using CWT (Continuous Wavelet Transform). Finally, features of the scalograms will be extracted by CNN. Two types of CNN architecture algorithms are used in this work for fault type detection, i.e., GoogLeNet and AlexNet. Accuracy of AlexNet architecture is better than GoogLeNet architecture for present faults classification problem.

Keywords— *convolution neural network (CNN), continuous wavelet transforms (CWT), GoogLeNet, AlexNet, Scalogram.*

Number: 10.14704/nq.2022.20.7.NQ33208

Neuro Quantology 2022; 20(7):1663-1668

I. INTRODUCTION

In distribution systems, the most frequently occurring fault is a single-line-to-ground fault. When such a fault occurs, to limit that current, arc suppression coil is used. On the other hand, it could enhance the complexity of faulty phase identification, and results to identify faulty phase characteristics will be weaker [1]. In [2], many protection techniques for line-to-ground fault have been introduced, which have been categorized into 3 classes. First is the Steady-State-Signal-Based Protection Method, second is Transient-State Signal-Based Protection Method & third, is Information-Fusion - Technology (IFT). First two methods have restrictions imposed by persuading architecture, multifaceted fault situation, faint fault current, electromagnetic ray interference, and other factors. By improvement of IFT (Information Fusion Technology), a combination of diversity of schemes like as Support Vector Machine (SVM) [37], Neural Network (NN) [4], Expert System, Fuzzy Theory, Genetic Algorithm (GA), CT (Clustering Technique) [5] has become more and more accepted to faulty phase identification.

In [6], to recognize the faulty phase, GNN (Genetic Neural Network) is introduced. In [7], SLG fault classifier is introduced, which uses a KNN algorithm in the regression model. A hybrid network enhanced major component investigation for feature extraction and selection, for fault detection, at that time, [8] the introduced technique is compared with fuzzy C-means algo based approaches and hierarchical [10] introduced a novel single line to ground faulty phase clustering algo to attain better classification accuracy in [9]. In identification method, which is without threshold setting.

Faulty phase identification has been attained by using working states in place of values of the setting system. Fuzzy C-means algo has divided an ongoing state of the sound phase into a faulty state and a healthy state.

In [129 [Bus paper.docx](#)], Bayesian Selectivity Technique-based and WT (Wavelet Transform) algos are introduced to detect the fault line. ANN scheme is using in a low current grounded network in favor of faulty phase detection. During the operation of an Artificial Neural Network approach, obtaining the classification results the procedure is, firstly to train input and output data by classification rules and testing a fault in a phase. As an alternative, it may efficiently differentiate faulty lines and healthy lines by using a huge amount of data for testing and training. On the other hand, for obtaining reasonable fault in the signal processing method, above methods are implemented [13]. Nowadays, a combination of machine learning models & wavelet transformation for pattern categorization & regression process is introduced.

In [14], authors described Nonnegative Matrix Factorization & Discrete Wavelet Packet Transform is implemented to increase speech. In [16], using directional wavelets, Deep Convolution Neural Network-based low-dose X-ray CT (Computed Tomography) reconstruction was introduced. In this work, CWT & CNN based fault detection methods for distribution systems are explained to resolve the problem of extracting & selecting features and classifying faulty phase and healthy phase. CWT and CNN can extract features for any faulty signals and then vigorously detect SLG fault using these features [15]. CWT filter bank is using to create scalograms of fault signals. For training, CNN models



like GoogLeNet and AlexNet are used. Complete detail is presented in the following sections.

II. MODEL OF IEEE-9 BUS SYSTEM

In this model, bus no. 1 has a swing generator of 16.5KV voltage, and values of active and reactive powers are 72.19MW and 29.8MVR respectively as shown in Fig. 1. Similarly, on bus

2, the voltage level is 18KV and on bus 3, it is 13.8KV. All remaining buses are at the 23KV voltage level. The total load connected to this system is 316MVA.

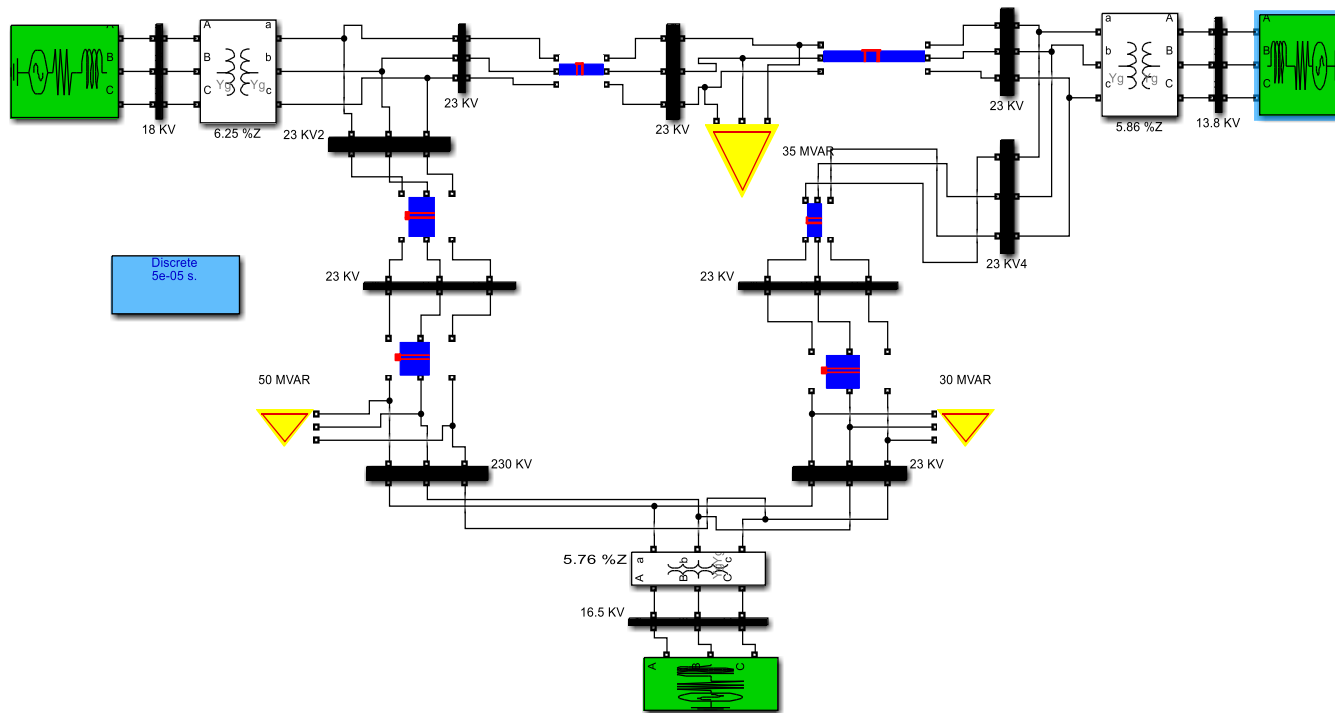


Fig. 1 Model of IEEE 9 bus ring Distribution system

III. METHODOLOGY

The GoogleNet (Inception) and AlexNet architectures are used for the identification of SLG faults. The flow chart shows the methodology of fault detection in distribution systems for SLG fault shown in fig. 2.

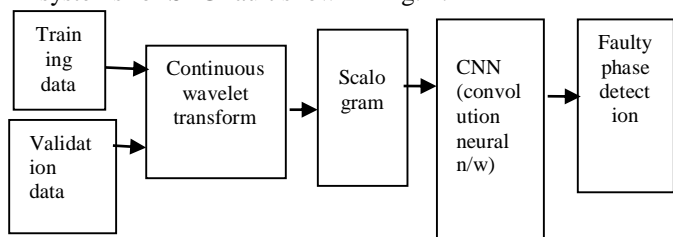


Fig. 2 flow chart of introducing a methodology

The projected work is divided into three steps. Step one is, to acquire zero sequence components of fault currents from the IEEE 9 Bus Distribution power system. Step two is, to convert data as a scalogram by using the CWT filter bank. In step three, scalograms are used as training as well as testing data for GoogleNet and Alexnet architecture. The networks classify the fault type i.e., AG (Phase A To

Ground), BG (Phase B To Ground), CG (Phase C To Ground). The scalograms dataset is split into two categories one is 80% for Training and the second is 20% for Validation.

A. GoogLeNet Inception Architecture:

GoogLeNet architecture uses three different filter sizes (i.e., 1*1, 3*3, 5*5) for same image and gets a vigorous output by combining features. GoogLeNet architecture consists of 144 layers and it has 4 million parameters which are very much less than from AlexNet which has approx. 60 million parameters. Convolution 1*1 is familiarized for reduction of dimensionality. AlexNet architecture determines ideal weight throughout training architecture and intuitively picks relevant characteristics.

Fig.3 shows multiple convolutions with three different size filters like 1x1 filter, 3x3 filter, 5x5 filter, and also max-pooling layer. Combination of multiple Inception modules to form a deeper network by which high accuracy can be obtained. Transfer learning provides new training for GoogLeNet and AlexNet Network to recognize single line to ground faults in IEEE 9Bus distribution systems. Image analysis pretrained network has been trained using numerous images to categorize different phases as phase A,



phase B, phase C of a single line to ground fault. Images are provided to the network as input data set, and there is the labeling of faulty phases in images making up output based on the probabilities of each of respective faulty phases.[16] Following four steps are involved in Classifying single line to ground Fault Image using GoogLeNet:

1. Loading Images:
2. Load GoogLeNet Network:
3. Freezing the Basic Layers:
4. Network Training:

second one is a validation set containing remaining 20% of an image data set. In second step, there is an employment of the “GoogLeNet layer Graph” to help in displaying layer information & architecture of the network. Fig.4 shows the 144 layers graph of GoogleNet architecture and provides all information on Bias, Weights for all convolutional layers. In the third step, GoogLeNet is starting to carry out retraining of new data sets. To set initial layers as zero layers. The step1665 of freezing layer enhances the network’s training speed. The size of input images for a GoogLeNet

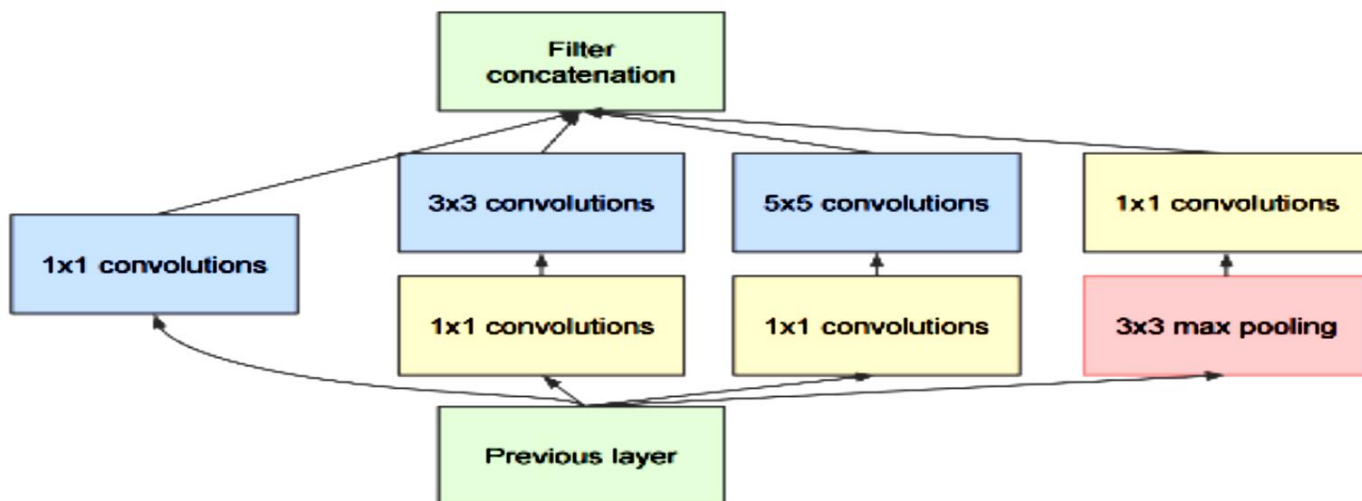


Fig. 3 GoogLeNet Inception Architecture with Dimensionality Reduction [12]

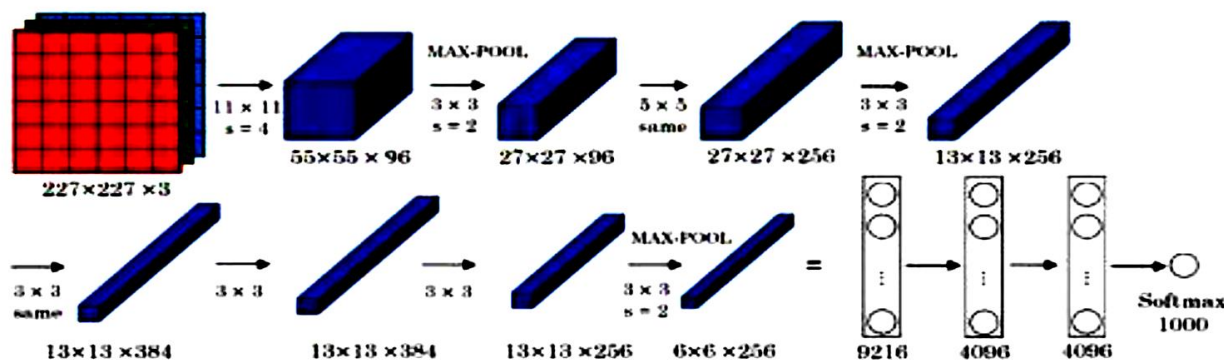


Fig. 4. Architecture of AlexNet [16]

In the first step loading a small set of image data of about 39 images. The data set is divided into two categories. The first is training that makes up 80% of an image data set, while the

Architecture is 224x224x3 (RGB image datastore). The image size can be restored by using an augmented image data store. Augmentation of data when it comes to the training of the network restricts overfitting while at the same



time keeping a memory of the characteristics of the training images. In step four trained network for 39 cases.[16]

B. AlexNet:

AlexNet was proposed by “Alex Krizhevsky”, “Ilya Sutskever”, & “Geoffrey Hinton” in 2012. AlexNet architecture is exceptionally bigger than LeNet architecture. This architecture comprises 25 layers. Three fully connected layers and five convolutional layers. In this architecture, ReLU activation is used. The input RGB images for AlexNet are of the size 227* 227* 3. The following four Steps are using in the Classification of single-line-to-ground fault using AlexNet Architecture.

1. Image Loading
2. Loading AlexNet
3. Substitution of the Final Layers
4. Training Network

The MATLAB function “splitEachLabel” divides this dataset into two categories. In which 1st is known as training and 2nd is known as validation category. Here 80% of image dataset split for training as well as remaining 20% for validating. In second step, load AlexNet Architecture by pretrained network. It will display information on network layer. Fig.4 illustrates flow chart of the AlexNet working process and exhibit weight, bias, stride, and padding used in convolutional, ReLU, max-pooling layers. [16]

The third step contains a substitution of the three layers with fully connected layers that include Classification output layer and a softmax layer. In MATLAB, the command imds - accumulate input images, layers - specify network architecture, options - “InitialLearnRate, MiniBatchsize, InitialLearnRate, MaxEpochs, ValidationData, ValidationFrequency, Plots, and Training-progress” are applied to identify faulty phases for various types of SLG fault.

IV. RESULTS

Observed waveforms are shown in fig. 5 for fault occurring at phases A, B & C respectively. These waveforms are drawn for 1000 starting samples of signal.

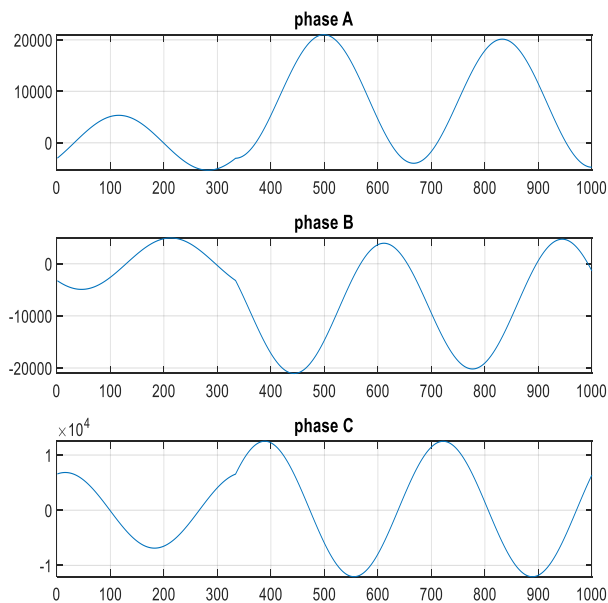


Fig. 5 voltage waveforms

Scalograms for 39 cases are made by CWT filterbank. For these scalograms, frequency 128Hz with signal length 1000samples, VoicesPerOctave 12 is used. Scalogram of phase A during a fault, shown in fig. 6

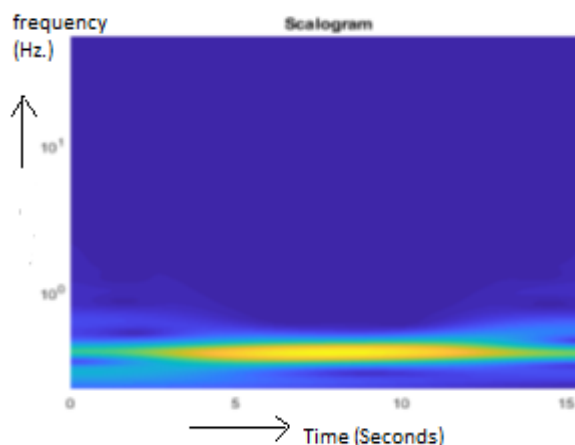


Fig: 6 Scalogram of phase A, voltage waveform during fault at phase A

Using two different types of CNN (Convolutional Neural Network), i.e. GoogLeNet and AlexNet, the accuracy in fault type detection is represented in figs. 7 & 8 respectively.



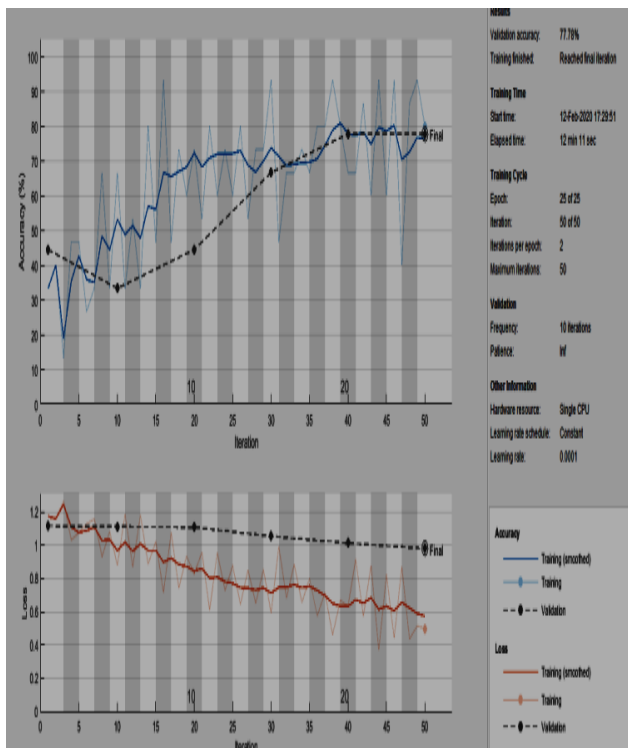


Fig. 7: Accuracy and loss graph of GoogLeNet

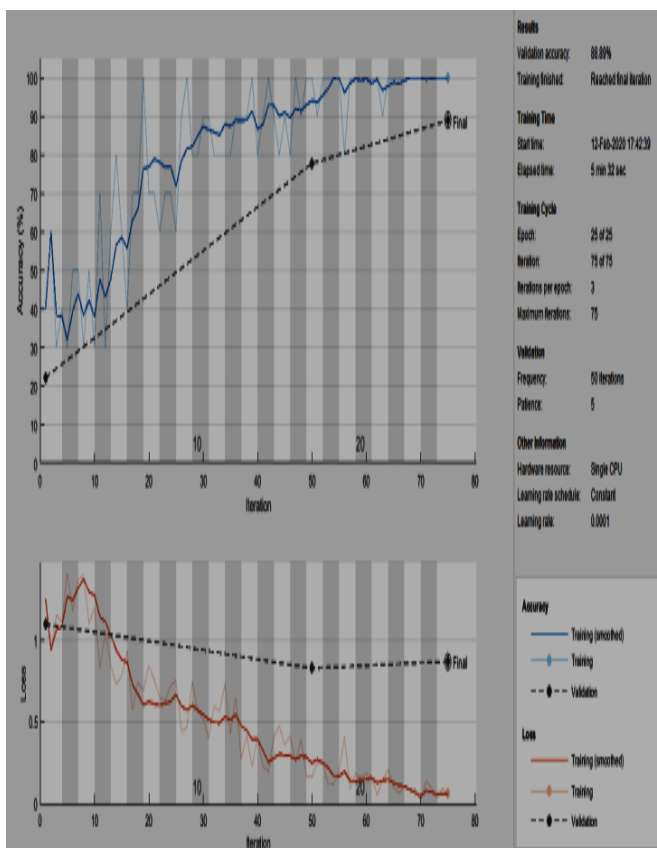


Fig. 8: Accuracy and loss graph of AlexNet

V. CONCLUSION

In this paper, CWT filter bank is used for time-frequency scalogram construction or RGB images of SLG fault signals of IEEE 9 Bus distribution systems. RGB scalogram images are taken as input data set of two types of Convolution Neural Network architecture, one is GoogLeNet, and the other is AlexNet. GoogLeNet as well as AlexNet architecture fault detection methods are introduced to resolve problems of selecting features and classify faulty phase and healthy phase. The trained Convolution Neural Networks have the advantage of extracting features from erroneous signals and accurately recognizing faulty phases A, B, and C all at the same time. For the current fault classification task, the accuracy of AlexNet architecture (88.89%) is higher than that of Google Net design (77.78%).

1667

REFERENCES

- [1] J.-A. Jiang, C.-L. Chuang, Y.-C. Wang, C.-H. Hung, J.-Y. Wang, C.-H. Lee, *et al.*, "A hybrid framework for fault detection, classification, and location—Part I: Concept, structure, and methodology," *IEEE Transactions on Power Delivery*, vol. 26, pp. 1988-1998, 2011.
- [2] Z. Zhixia, L. Xiao, and P. Zailin, "Fault line detection in neutral point ineffectively grounding power system based on phase-locked loop," *IET Generation, Transmission & Distribution*, vol. 8, pp. 273-280, 2014.
- [3] Y. Wang, J. Zhou, Z. Li, Z. Dong, and Y. Xu, "Discriminant-analysis-based single-phase earth fault protection using improved PCA in distribution systems," *IEEE Transactions on Power Delivery*, vol. 30, pp. 1974-1982, 2015.
- [4] N. I. Elkalashy, N. G. Tarhuni, and M. Lehtonen, "Simplified probabilistic selectivity technique for earth fault detection in unearthed MV networks," *IET generation, transmission & distribution*, vol. 3, pp. 145-153, 2009.
- [5] A. Ghaderi, H. A. Mohammadpour, H. L. Ginn, and Y.-J. Shin, "High-impedance fault detection in the distribution network using the time-frequency-based algorithm," *IEEE Transactions on Power Delivery*, vol. 30, pp. 1260-1268, 2014.
- [6] T. Ji, Q. Pang, and X. Liu, "Study on fault line detection based on genetic artificial neural network in compensated distribution system," in *2006 IEEE International Conference on Information Acquisition*, 2006, pp. 1427-1431.
- [7] X. Deng, R. Yuan, Z. Xiao, T. Li, and K. L. L. Wang, "Fault location in loop distribution network using SVM technology," *International Journal of Electrical Power & Energy Systems*, vol. 65, pp. 254-261, 2015.
- [8] X. Zeng, K. Yu, Y. Wang, and Y. Xu, "A novel single phase grounding fault protection scheme without threshold setting for neutral ineffectively earthed power systems," *CSEE Journal of Power and Energy Systems*, vol. 2, pp. 73-81, 2016.
- [9] Y. Y. Wang, X. J. Zeng, Z. Y. Dong, Y. Xu, J. Yuan, and Y. Huang, "Stator single-phase-to-ground fault protection for bus-connected powerformers based on hierarchical clustering algorithm," *IEEE Transactions on Energy Conversion*, vol. 28, pp. 991-998, 2013.
- [10] M. Farshad and J. Sadeh, "Accurate single-phase fault-location method for transmission lines based on k-nearest neighbor algorithm using one-end voltage," *IEEE Transactions on Power Delivery*, vol. 27, pp. 2360-2367, 2012.
- [11] Z. Shao, L. Wang, and H. Zhang, "A fault line selection method for small current grounding system based on big data," in *2016*



- IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, 2016, pp. 2470-2474.
- [12] N. I. Elkalashy, A. M. Elhaffar, T. A. Kawady, N. G. Tarhuni, and M. Lehtonen, "Bayesian selectivity technique for earth fault protection in medium-voltage networks," *IEEE Transactions on Power Delivery*, vol. 25, pp. 2234-2245, 2010.
- [13] S.-S. Wang, A. Chern, Y. Tsao, J.-w. Hung, X. Lu, Y.-H. Lai, et al., "Wavelet speech enhancement based on nonnegative matrix factorization," *IEEE Signal Processing Letters*, vol. 23, pp. 1101-1105, 2016.
- [14] T. Cui, X. Dong, Z. Bo, and A. Juszczyk, "Hilbert-transform-based transient/intermittent earth fault detection in noneffectively grounded distribution systems," *IEEE Transactions on Power Delivery*, vol. 26, pp. 143-151, 2010.
- [15] M.-F. Guo and N.-C. Yang, "Features-clustering-based earth fault detection using singular-value decomposition and fuzzy c-means in resonant grounding distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 93, pp. 97-108, 2017.
- [16] E. Kang, J. Min, and J. C. Ye, "A deep convolutional neural network using directional wavelets for low - dose X - ray CT reconstruction," *Medical physics*, vol. 44, pp. e360-e375, 2017.

