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Review on Fault Detection and Classification in Transmission Line using Machine Learning Methods

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***Abstract*—Fast and precise fault categorization, location estimate, and fault detection are crucial because persistent faults can interrupt the power supply. The power outage zone will extend to nearby areas after the fault incident. Accurate and prompt fault identification is required for a power system to return to a healthy state. Protection, fault detection, diagnosis, identification, and localization are essential for efficient working of power system. Transmission line(TL) extensions are necessary due to rising industrialization and power demand, which greatly increases the complexity of the power system network. Analysis of faults in this intricate network becomes challenging. This paper reviews the latest machine-learning methods used for the identification and classification of faults in power systems.**

***Index Terms*—Fault Detection (FD), Power Systems, Machine Learning**

I. Introduction

ELECTRICITY has become an essential aspect of our daily lives, powering our modern society. An electrical power system can be divided into generation, transmission, and distribution [1]. The power system network is becoming increasingly complicated and vulnerable to electrical failures or disruptions due to the rising demand for electricity [2]. Transmission lines (TL), which are open to a variety of environmental factors as well as animal or human contacts, account for 80% of the faults int the network [3,4]. Short circuit (SC) problems account for most of the transmission line faults [5]. The daily operation involves dealing with several different kinds of SC faults, which can be sorted into symmetrical and unsymmetrical problems. Triple line to ground (L-L-L-G) and triple line (L-L-L) faults are examples of symmetrical faults that preserve the system's balance. Even though they have a low chance of occurrence, they are the most extreme kind of short-circuit faults due to their significant effects and potential for equipment damage. The double line to ground (L-L-G), line to ground (LG), and line-to-line (L-L) faults are the asymmetrical or unbalanced faults which cause an imbalance in the electricity system during the fault. Despite being less severe than balanced ones, single line to ground faults give have a higher probability of occurrence [6]. The voltage and current signals of a three-phase TL diverge from their reference values during a fault, which can have disastrous effects if they are not corrected in a timely manner [7]. As a result, fault analysis has developed into an important research platform for power engineers.

The main objectives of fault-detection methods [8] are :

1) fault classification, which involves being able to recognise the fault type and also phase with the fault, and
2) fault location, which involves being able to precisely estimate the length of a TL along which the fault has occurred.

Single-line techniques may achieve both objectives, while power system fault-diagnostic techniques only yield estimates of the faulted parts [9]. Feature extraction is commonly used in fault detection and diagnostic techniques to combine the pertinent and essential data from the raw signals. The post-fault transient voltage or current signals in TL faults contain the crucial fault data [10]. Due to their precision and speed, modern fault diagnosis approaches based on signal processing and machine learning tools have gained popularity. Machine learning (ML) techniques lessen reliance on previous expert knowledge and get around the drawbacks of traditional expert systems. Their strong generalisation capacity, which allows them to apply the discovered patterns to new data samples, enables the power system to work well for unseen data as well. Since it is frequently hard to train for every single possible fault circumstance, the generalisation ability is very helpful for fault-diagnosis issues [11].The paper summarizes on the feature extraction methods for analyzing the fault signals and also discusses the latest machine learning methods that are used in fault diagnosis.

An overview of defects and fault categorization in transmission lines is given in section I. Section II describes the various feature extraction approaches used in identifying and categorising defects. The machine learning techniques are briefly described in Section III. In-depth analysis and comparison of current ML techniques for the detection, categorization, and localization of transmission line faults are covered in Section IV. The paper concludes with identifying the drawbacks and challenges of the methods developed.

II. Feature Extraction

Fault signals in transmission lines can be classified as :

1) Three Phase to Ground Fault

2) Three Phase Fault
3) Double Line to Ground Fault
4) Line to Line Fault
5) Single Line to Ground Fault and,
6) System with no fault

Figures (1-12) show an example of the current waveforms when the system experiences various fault connections, where A, B, and C represent each of the phases. This shows that during a fault event, the current is very large for a short amount of time.

The fault categorization technique is separated into three steps. First, the signal analysis method is used to process the voltage and current defect signals. Second, the properties of the processed signals are retrieved. The trained model receives the characteristics, and the classification outcomes are then obtained. To analyse voltage and current fault signals, the S-transform (ST), Wavelet Transform (WT), and Fast Fourier Transform (FFT) are used. The characteristic used for classification is typically one or more characteristics of the fault signals. The fault classifier uses supervised learning methods for the categorization [12].

Although Discrete Wavelet Transform (DWT) has superior time-frequency resolution, both DWT and ST are very effective signal processing methods for extracting characteristics from fault signals. Due to the enormous number of features that DWT and ST both produce, they must be efficiently merged in order to decrease the amount of features without sacrificing the information about defects. For fault analysis, various metrics from the DWT coefficients are used [13].

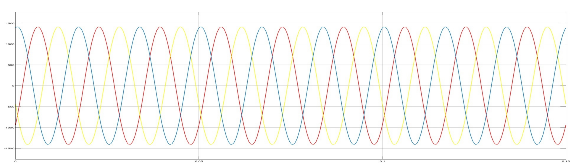

Fig. 1: System with no Fault

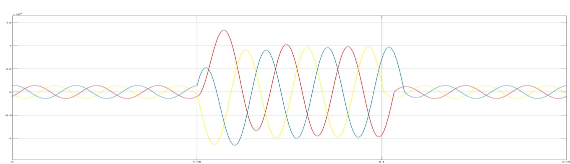

Fig. 2: System With ABC-G Fault

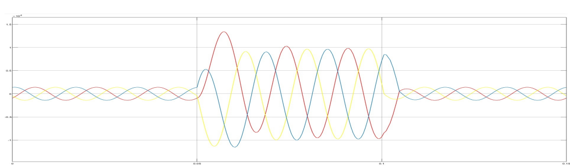

Fig. 3: System with ABC Fault

With a rise in signal frequency, DWT's time-frequency resolution falls off. Wavelet Packet Decomposition (WPD)

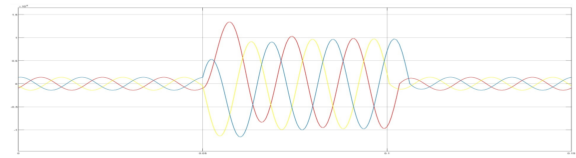

Fig. 4: System with AB-G Fault

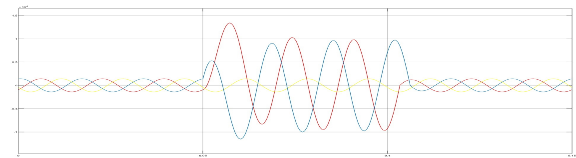

Fig. 5: System with AC-G Fault

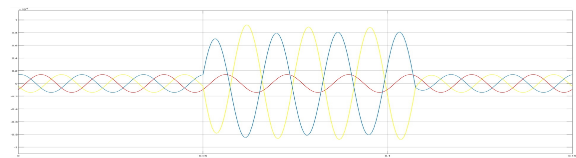

Fig. 6: System with BC-G Fault

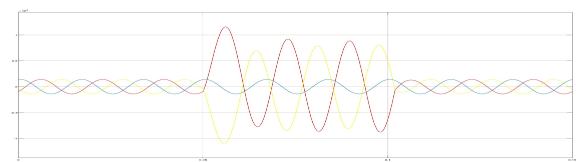

Fig. 7: System with AB Fault

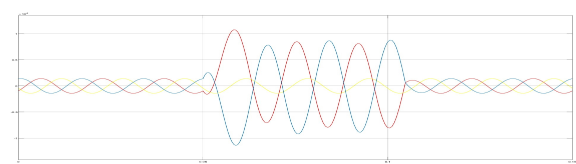

Fig. 8: System with AC Fault

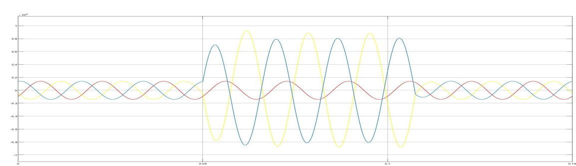

Fig. 9: System with BC Fault

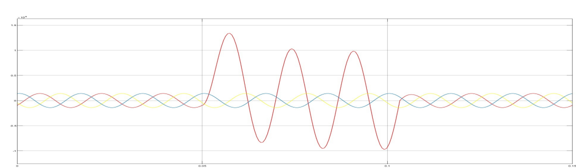

Fig. 10: System with A-G Fault

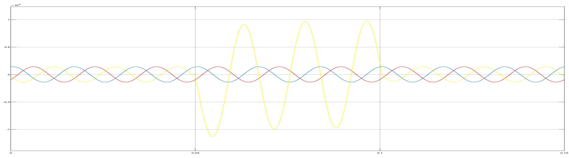

Fig. 11: System with B-G Fault

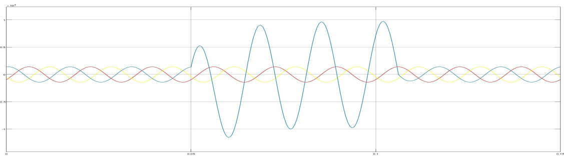

Fig. 12: System with C-G Fault

improves the time-frequency resolution of DWT for higher frequency signals, making it a useful signal processing method for isolating features from transients. A travelling wave method based on WPD was used in [14] to locate lightning-induced faults. The strength of WPD values at each node in a series compensated line is taken as a feature for training support vector regression to assess the position of the defect [15], even though the results of just two fault locations are given in this study.

It is thought that Shanon's entropy with the WT provides an efficient way to express the features [16]. The concept of turning signals into visual cues has attracted a lot of attention since it might be used to implement modern fault analysis jobs [11,12]. The data can be represented graphically, which reveals more expensive defect features and supports the generalizability of classification performance. The characteristics of the fault signals were extracted using the Hilbert Huang Transform (HHT) in [12]. This was used to eliminate the challenge of selecting a suitable mother wavelet for a WT.

III. Machine Learning Methods

Machine Learning (ML) methods can be classified as supervised or unsupervised learning methods. In supervised learning, the ML task assigns each input value to the required class label [17]. Supervised learning algorithms are generally classified into regression and classification. In unsupervised learning, ML models find the hidden patterns and perceptions from the given data by themselves. Some of the popular unsupervised learning algorithms are K-means clustering, KNN, Hierarchical Clustering, Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Neural Networks etc [18].

IV. Recent Developments in Fault Classification

A basic methodology of fault analysis using any ML method is as shown in Fig.5 The transmission line is modelled based on the real system parameters and the environmental conditions for fault analysis. The fault is generated in the system. A, B, C, and G are used to represent the three phases and the ground. For feature extraction, the data gained from fault production is employed. A ML model is trained and tested

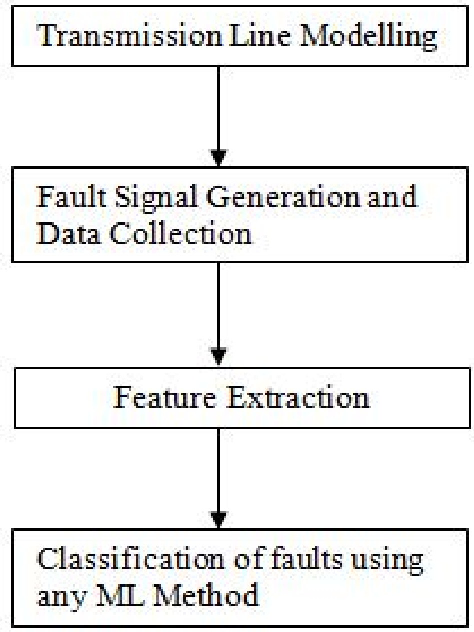

Fig. 13: Basic Methodology for Fault Analysis

using the features that were gathered, and it then accurately categorizes the fault. A large transient current is generated in the system when a fault occurs. This current waveform exhibits higher frequency over a brief period of time.

With the help of this data extraction, we could get the features required for ML model.

For the detection, classification, and estimation of fault location at any random position on a transmission line for both type of low and high fault impedances, Bikash *et al* [19] used Wavelet Packet Entropy (WPE) and an Radial Basis Function Neural Network (RBFNN). RBFNN's output layer outputs for classification and estimation of fault location, while its input layer has 12 inputs. The activation function has been proposed to be the Gaussian radial basis function. About 98% of faults were correctly classified. However, one of the single line (A-G) faults had an accuracy of roughly 93%, and for other faults as well, the accuracy varied from fault to fault.

P.Balakrishnan *et al* [13] introduced a DWT based algorithm for overhead lines. DWT was employed with "db6" as the mother wavelet. A ground threshold value served as the basis for the classification procedure. Issues can be discovered by receiving fault information along the entire transmission system, from the regional terminal end to the initial terminal end. All eleven categories of TL faults were detected, classified, and located using DWT to identify the signal, extract the detail coefficient, and then locate the faults. The threshold value used for classification varies with different systems.

Shahriar *et al* [20] offered an unsupervised framework based on a Capsule Network (CN) for identifying and categorising TL defects. It was done using a sparse filtering extension to CN. By actively learning the critical defect characteristics,

Author	Publication	Method Used	Results & Accuracy
Bikash Patel *et al* [19]	Electric Power Components and Systems	Wavelet Packet Entropy and RBFNN Based	About 98% accurate in fault identification and Error in fault localization about 0.2%
P.Balakrishnan *et al* [13]	IJEAT	Discrete Wavelet Transform	Fault Detection Time - 1.4s
Shabriar Rahman *et al* [20]	Elsevier	Capsule Network Sparse Filtering based	99% against noises, and 97% against the high impedance faults and line parameters variation
Daniel Gutierrez-Rojas *et al* [21]	Springer	DFT for preprocessing	Deep neural networks - 98.33% and QARMA - 98% Accuracy
Pathomthat Chiradeja *et al* [22]	IEEE	Discrete Wavelet Transform	Cannot be applied for complex networks
Nguyen Nhan Bon *et al* [23]	IJEAT	Hybrid of Wavelet Transform,GoogLeNet and CNN	Average error in fault location is 0.215
Yann Qi Chen *et al* [10]	IEEE	SW-ELM,SG-ELM based	Classification accuracy for SW-ELM :98.22% SG-ELM:98.16%
Mou Fa Guo *et al* [12]	IEEE	Hilbert Huang Transform and CNN	Accuracy varies between 98% and 99% under varoius conditions
Fezan Rafique *et al* [24]	Elsevier	LSTM based	99% accuracy
Praveen Rai *et al* [25]	Elsevier	CNN	Accuracy 99.52%
Ji Han *et al* [26]	IEEE	Improved CNN	Accuracy 95% , but drops with noise
Yanhai Wang *et al*[27]	Elsevier	Image based SVM classification	Accuracy - about 95% , low accuracy for L-G fault detection
Arash *et al*[28]	Elsevier	C-LSTM based	Accuracy-About 97%
Yanhui Xi *et al*[29]	Elsevier	SA-MobileNetV3 based	Accuracy-99.90%
Muhammad Sarwar *et al* [31]	Elsevier	PCA, FDA and SVM based	PCA - detect fault, FDA - isolate fault, easy classification of HIFs

TABLE I: Comparison of Recent Methods

the capsule network with sparse filtering (CNSF) improves model performance without needing a substantial amount of information. The proposed technique acquires cycle post-fault three-phase data and decodes it into a single image, which is the feed of the considered CNSF model. Four distinct topologies were used to support the proposed CNSF model's efficacy. But it was not consistent in the analysis because of the diversity in transmission line topologies, system parameters, and operating conditions.

Daniel *et al* [21] studied a fault selection system for double-circuit transmission lines using various learning techniques. The suggested method preprocesses the transmission line's raw data using the Discrete Fourier Transform (DFT) before feeding it to the learning algorithm, which uses a training period to identify and categorise any faults. Then, using simulations, the effectiveness of various machine learning algorithms was numerically compared. In the comparison, an accuracy of 98.47% was found to be achieved by an artificial neural network (ANN). The ANN method's shortcomings include its inability to produce results that can be explained and its lack of robustness to noisy measurements.

Pathomthat *et al* [22] analysed faults in a transmission line and high voltage capacitor banks using DWT. The findings showed that when compared to failures occurring in a capacitor bank, the features of system parameters in the event of transmission line faults are distinct. DWT was also used to resolve the disagreement between system characteristics in cases when failures occurred in both a single capacitor bank and two capacitor banks linked in a back-to-back topology. But the method cannot be applied to complex networks.

Nguyen *et al* [23] created a hybrid approach based on machine learning (ML) techniques to recognise, categorise, and find electrical defects on transmission lines. First, characteristics from the current or voltage signals were extracted using the WT approach. Eleven coefficients were created by decomposing the extracted signals. The data of various fault kinds were transformed to an RGB image, and these coefficients were calculated according to the energy level.

Second, the fault is classified using the GoogLeNet model, and the fault's location is suggested using the Convolutional Neural Network (CNN) method.

Summation-Wavelet Extreme Learning Machine (SW-ELM) is a ML method that incorporates feature extraction in the learning process, was used by Yann Qi Chen *et al* [10] to offer an integrated framework integrating fault classification and location. Additionally, the summation-Gaussian extreme learning machine (SG-ELM), which was proposed and successfully applied to transmission line fault diagnosis, was developed as an extension of the SW-ELM. Due to its comprehensive self-learning capabilities and lack of ad hoc feature extraction requirements, SG-ELM may be deployed with the least amount of expert subjectivity. But it was unaffected by changes in the fault inception angle.

The HHT band-pass filter was used by Mou Fa Guo *et al* [12] to create the time-frequency energy matrix from recorded fault waveform. For fault classification, a CNN based technique for image similarity identification is utilised. The nonstatonary and nonlinear signal can be analysed using the HHT. The Hilbert transform and the empirical mode decomposition (EMD) are its two component phases. The original fault voltage and current signals are divided into a number of Intrinsic Mode Functions (IMF) using the EMD. Then, each IMF is subjected to the Hilbert transform, yielding the time-frequency plot of the fault signals.However, accuracy is poor for B-G faults in noisy environments. Additionally, the distribution generator access affects the accuracy rate for two phase short circuits.

Fezan *et al* [24] suggested a technique that uses Long Short Term Memory (LSTM) units acting directly on operational information rather than characteristics. The method employs the temporal sequence of the operational information of the power network to build an "end to end" model. End-to-end learning eliminates the requirement for time-consuming feature extraction by learning directly from the labelled datasets. This quickens decision-making.

Use of Distribution Generators (DG) has been increasing in the distribution systems, which results in conventional methods of relaying operations not suitable for changing fault current levels. In [25], Praveen *et al* customised CNN for fault classification in the distribution networks with DGs. The developed model doesn't need any preprocessing, which makes it efficient during the testing period.

Ji Han *et al* [26] suggested an unique diagnosis model for power systems to reduce the need for constant model modification effort when the system topology changes. The gradient similarities among the multichannel electrical signals were first converted to the visible similarity pictures, which were then given to the neural network. This data preprocessing method uses gradient computation and similarity evaluation. Then the CNN used Spatial Pyramid Pooling (SPP) and Hashing Classifier (HC). Even when there are topological changes in the power systems, the fault-diagnosis model's structure can be kept constant with the help of the SPP and HC approaches. But the accuracy seems to drop with noise.

Yanhai Wang *et al* [27] used a quality-aware fine-grained-based image classification for transmission line fault detection. This method was used to detect the fault zone. The technique uses wavelet-based support vector machines and quality-based discriminative feature extraction to extract the characteristics of line currents by leveraging Fast R-CNN-based image samples decomposition, where the quality module is used to select the most discriminative regions. The retrieved features are then used to train an SVM to identify the issue. The suggested method didn't work well for the L-G fault.

Frequency Response Analysis (FRA) was used by Arash *et al* in [28] to assess the effects of impedance and to identify the fault location when a fault occurs. Since the interpretation of FRA is weak, Convolutional Long Short Term Memory was proposed to extract the features of frequency response curves for each fault.

Yanhui Xi *et al* developed a fault classification method based on SA-MobileNetV3 [29]. The method is similar to image recognition. The three phase current and voltage signals are transformed into two dimensional images based on Continuous Wavelet Transform (CWT). Then the proposed method is used in classifying the faults.

Apart from the above discussed faults, High Impedance Faults (HIF) occur in TLs. They are caused when a conductor comes in contact with trees or can be due to broken conductors. These kinds of faults can inflict fire risks and also electrical shocks that may endanger the lives of living beings [30]. In [31], Sarwar *et al* suggested methods that use the information from voltage and current sensors to accurately detect and isolate HIFs in distribution networks. These information based techniques used for detection were PCA, Fisher Discriminant Analysis (FDA), and Support Vector Machine(SVM). PCA was able to successfully detect HIFs, while FDA was able to classify/locate HIFs.

V. Conclusion

The paper analyzes various ML methods for fault detection in power systems. Accurate classification of faults in transmission lines using WTs requires varying their parameters according to the power system topology. And also, there is a need to choose appropriate mother wavelet analysis whenever the fault is needed to be analysed. Mostly daubechies or Morlet wavelet are chosen as the mother wavelet for the analysis. This lead to the need for a more generalized fault classification . Machine learning methods were employed due to their generalization property after training from a larger set of data values. The data for training the model were obtained by preprocessing the signal. The features can be extracted by using any of the signal processing methods such as WT, FFT, HHT etc. Some methods use the energy values from the faulty signals to convert them into a proportional pixel value,where these image matrices are used as features for fault analysis. Even though classifications with high accuracy are obtained through these models, the methods so far don't consider the interdependency between the networks when analysing the faults that occurred. Certain faults occur for a very short period of time and doesn't affect the performance of systems. The fault time should also be considered for further studies.

REFERENCES

[1] J. Morais, Y. Pires, C. Cardoso and A. Klautau, "A Framework for Evaluating Automatic Classification of Underlying Causes of Disturbances and Its Application to Short-Circuit Faults," in IEEE Transactions on Power Delivery, vol. 25, no. 4, pp. 2083-2094, Oct. 2010, doi: 10.1109/TPWRD.2010.2052932.

[2] J. C. Arouche Freire, A. R. Garcez Castro, M. S. Homci, B. S. Meiguins and J. M. De Morais, "Transmission Line Fault Classification Using Hidden Markov Models," in IEEE Access, vol. 7, pp. 113499-113510, 2019, doi: 10.1109/ACCESS.2019.2934938.

[3] Aleem, S.A., Shahid, N. Naqvi, I.H. Methodologies in power systems fault detection and diagnosis. Energy Syst 6, 85–108 (2015). https://doi.org/10.1007/s12667-014-0129-1

[4] K. Chen, J. Hu, Y. Zhang, Z. Yu and J. He, "Fault Location in Power Distribution Systems via Deep Graph Convolutional Networks," in IEEE Journal on Selected Areas in Communications, vol. 38, no. 1, pp. 119-131, Jan. 2020, doi: 10.1109/JSAC.2019.2951964.

[5] S.S. Gururajapathy, H. Mokhlis, H.A. Illias, Fault location and detection techniques in power distribution systems with distributed generation: A review, Renewable and Sustainable Energy Reviews, Volume 74, 2017, Pages 949-958, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2017.03.021. (https://www.sciencedirect.com/science/article/pii/S1364032117303386)

[6] M. Farshad, J. Sadeh, Fault locating in high-voltage transmission lines based on harmonic components of one-end voltage using random forests, Iran. J. Electr. Electron. Eng. 9 (3) (2013) 158–166.

[7] A. Saber, A. Emam and H. Elghazaly, "A Backup Protection Technique for Three-Terminal Multisection Compound Transmission Lines," in IEEE Transactions on Smart Grid, vol. 9, no. 6, pp. 5653-5663, Nov. 2018, doi: 10.1109/TSG.2017.2693322.

[8] Korbicz, Józef, et al., editors. "Fault Diagnosis." Models, Artificial Intelligence, Applications, Springer, 2003. Bowker, https://doi.org/10.1007/b1091310.1007/978-3-642-18615-8.

[9] W. A. dos Santos Fonseca, U. H. Bezerra, M. V. A. Nunes, F. G. N. Barros and J. A. P. Moutinho, "Simultaneous Fault Section Estimation and Protective Device Failure Detection Using Percentage Values of the Protective Devices Alarms," in IEEE Transactions on Power Systems, vol. 28, no. 1, pp. 170-180, Feb. 2013, doi: 10.1109/TPWRS.2012.2207747.

[10] Y. Q. Chen, O. Fink and G. Sansavini, "Combined Fault Location and Classification for Power Transmission Lines Fault Diagnosis With Integrated Feature Extraction," in IEEE Transactions on Industrial Electronics, vol. 65, no. 1, pp. 561-569, Jan. 2018, doi: 10.1109/TIE.2017.2721922.

[11] K. Chen, J. Hu and J. He, "Detection and Classification of Transmission Line Faults Based on Unsupervised Feature Learning and Convolutional Sparse Autoencoder," in IEEE Transactions on Smart Grid, vol. 9, no. 3, pp. 1748-1758, May 2018, doi: 10.1109/TSG.2016.2598881.

[12] M. -F. Guo, N. -C. Yang and W. -F. Chen, "Deep-Learning-Based Fault Classification Using Hilbert–Huang Transform and Convolutional Neural Network in Power Distribution Systems," in IEEE Sensors Journal, vol. 19, no. 16, pp. 6905-6913, 15 Aug.15, 2019, doi: 10.1109/JSEN.2019.2913006.

[13] Transmission line fault detection, classification and location using wavelet transform. (2019). International Journal of Engineering and Advanced Technology, 8(6S3), 1770-1775. https://doi.org/10.35940/ijeat.f1337.0986s319

[14] C. Yao, W. Hao, Y. Long, Y. Mi, Y. Ma, Y. Shen, and L. Wang, "A novel method to locate a fault of transmission lines by shielding failure," IEEE Trans. Dielectr. Electr. Insul., vol. 21, no. 4, pp. 1573–1583, August 2014. doi: 10.1109/TDEI.2014.004321

[15] A. A. Yusuff, C. Fei, A. A. Jimoh, and J. L. Munda, "Fault location in a series compensated transmission line based on wavelet packet decomposition and support vector regression," Electr. Power Syst. Res., vol. 81, no. 7, pp. 1258–1265, 2011. doi: 10.1016/j.epsr.2010.12.016.

[16] Z. Liu, Z. Han, Y. Zhang and Q. Zhang, "Multiwavelet Packet Entropy and its Application in Transmission Line Fault Recognition and Classification," in IEEE Transactions on Neural Networks and Learning Systems, vol. 25, no. 11, pp. 2043-2052, Nov. 2014, doi: 10.1109/TNNLS.2014.2303086.

[17] S. V. Mahadevkar et al., "A Review on Machine Learning Styles in Computer Vision—Techniques and Future Directions," in IEEE Access, vol. 10, pp. 107293-107329, 2022, doi: 10.1109/ACCESS.2022.3209825.

[18] "Machine Learning: What It Is, Tutorial, Definition, Types - Javatpoint." www.javatpoint.com, www.javatpoint.com/machine-learning. Accessed 30 Jan. 2023.

[19] Bikash Patel, Parthasarathi Bera Binoy Saha (2018) Wavelet Packet Entropy and RBFNN Based Fault Detection, Classification and Localization on HVAC Transmission Line, Electric Power Components and Systems, 46:1, 15-26, DOI: 10.1080/15325008.2018.143181

[20] Fahim, S. R., Sarker, S. K., Muyeen, S., Das, S. K., Kamwa, I. (2021). A deep learning based intelligent approach in detection and classification of transmission line faults. International Journal of Electrical Power Energy Systems, 133, 107102. https://doi.org/10.1016/j.ijepes.2021.107102

[21] Rojas, D., Christou, I. T., Dantas, D., Narayanan, A., Nardelli, P. H., Yang, Y. (2022). Performance evaluation of machine learning for fault selection in power transmission lines. Knowledge and Information Systems, 64(3), 859-883. https://doi.org/10.1007/s10115-022-01657-w

[22] P.Chiradeja and A. Ngaopitakkul, "Analyzing the Characteristics of Faults in a Transmission Line and High Voltage Capacitor Banks in a 115-kV-Power System Using Discrete Wavelet Transform," in IEEE Access, vol. 10, pp. 86765-86781, 2022, doi: 10.1109/ACCESS.2022.3199362

[23] Bon, N. N., Dai, L. V. (2022). Fault identification, classification, and location on transmission lines using combined machine learning methods. International Journal of Engineering and Technology Innovation, 12(2), 91-109. https://doi.org/10.46604/ijeti.2022.7571

[24] Fezan Rafique, Ling Fu, Ruikun Mai, End to end machine learning for fault detection and classification in power transmission lines, Electric Power Systems Research, Volume 199, 2021, 107430, ISSN 0378-7796, https://doi.org/10.1016/j.epsr.2021.107430

[25] Praveen Rai, Narendra D. Londhe, Ritesh Raj, Fault classification in power system distribution network integrated with distributed generators using CNN, Electric Power Systems Research, Volume 192, 2021, 106914, ISSN 0378-7796, https://doi.org/10.1016/j.epsr.2020.106914. (https://www.sciencedirect.com/science/article/pii/S0378779620307124)

[26] J. Han, S. Miao, Y. Li, W. Yang and H. Yin, "Fault Diagnosis of Power Systems Using Visualized Similarity Images and Improved Convolution Neural Networks," in IEEE Systems Journal, vol. 16, no. 1, pp. 185-196, March 2022, doi: 10.1109/JSYST.2021.3056536.

[27] Yanhai Wang, Qingquan Li, Bo Chen, Image classification towards transmission line fault detection via learning deep quality-aware fine-grained categorization, Journal of Visual Communication and Image Representation, Volume 64, 2019, 102647, ISSN 1047-3203, https://doi.org/10.1016/j.jvcir.2019.102647. (https://www.sciencedirect.com/science/article/pii/S1047320319302688)

[28] Arash Moradzadeh, Hamid Teimourzadeh, Behnam Mohammadi-Ivatloo, Kazem Pourhossein, Hybrid CNN-LSTM approaches for identification of type and locations of transmission line faults, International Journal of Electrical Power Energy Systems, Volume 135, 2022, 107563, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2021.107563. (https://www.sciencedirect.com/science/article/pii/S0142061521007973)

[29] Yanhui Xi, Weijie Zhang, Feng Zhou, Xin Tang, Zewen Li, Xiangjun Zeng, Pinghua Zhang, Transmission line fault detection and classification based on SA-MobileNetV3, Energy Reports, Volume 9, 2023, Pages 955-968, ISSN 2352-4847, https://doi.org/10.1016/j.egyr.2022.12.043. (https://www.sciencedirect.com/science/article/pii/S2352484722026439)

[30] Ying-Yi Hong, Wei-Shun Huang, "Locating High-Impedance Fault Section in Electric Power Systems Using Wavelet Transform, -Means, Genetic Algorithms, and Support Vector Machine", Mathematical Problems in Engineering, vol. 2015, Article ID 823720, 9 pages, 2015. https://doi.org/10.1155/2015/823720

[31] Muhammad Sarwar, Faisal Mehmood, Muhammad Abid, Abdul Qayyum Khan, Sufi Tabassum Gul, Adil Sarwar Khan, High impedance fault detection and isolation in power distribution networks using support vector machines, Journal of King Saud University - Engineering Sciences, Volume 32, Issue 8, 2020, Pages 524-535, ISSN 1018-3639, https://doi.org/10.1016/j.jksues.2019.07.001. (https://www.sciencedirect.com/science/article/pii/S1018363919302004)