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Remote Fault Identification and Analysis in Electrical Distribution Network Using Artificial Intelligence

Dr. N M G Kumar[1], Dr. A. Hema Sekhar[2], Dr. K. Balaji Nanda Kumar Reddy[3], Angulakshmi M[4] and Dr. Devangkumar Umakant Shah[5]

[1]Professor, Department of Electrical and Electronics Engineering, Mohan Babu University, Sree Vidyanikethan Engineering College, Tirupathi, Andhra Pradesh, 517102, nmgkumar@gmail.com

[2]Professor and HOD, Department of EEE, VEMU Institute of Technology, P. Kothakota, Chittoor, Andhra Pradesh, India, ahemasekar@yahoo.com

[3]Associate Professor, Department of EEE, Annamacharya Institute of Technology & Sciences, Tirupati, Andhra Pradesh, India, balajinkr@gmail.com

[4]Assistant Professor, School of Information Technology and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, angulakshmi.m@vit.ac.in

[5]Principal and Professor, Department of Electrical Engineering, K. J. Institute of Engineering & Technology, Savli, Vadodara, dushah88@gmail.com

***Correspondence:** Dr. N M G Kumar; nmgkumar@gmail.com

ABSTRACT- This research describes a method for wavelet decomposition and machine learning-based fault site classification in a radial power distribution network. The first statistical observation is produced using wavelet decomposition and wavelet-based detailed coefficients in terms of Kurtosis and Skewness parameters. For this objective, six distinct machine learning methods are deployed. They are evaluated and compared using unknown data sets with varying degrees of unpredictability. One approach has been shown to be the most accurate in locating the location of the problem bus.

General Terms: Artificial Intelligence, Network Modelling, Fault Discrimination.
Keywords: Discrimination, Kurtosis, Machine learning, Radial network, Remote fault location, Skewness.

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1. INTRODUCTION

In general, electric power or electricity must be created and distributed through a network, where continuity, security, and stability become the most critical issues. The modern power system network is growing more complicated. In this setting, defect identification looks to be a difficult task for Power Engineers. Many studies have been conducted on various aspects of network faults, and numerous approaches for detecting various sorts of faults have been developed.

To ensure an uninterrupted supply of energy, it is now necessary to continually check the voltage, current, and other network characteristics. Condition monitoring and defect detection are generally carried out in practice based on this. Y. Q. Chen et al. (2018) proposed an integrated technique for feature extraction to categorise various kinds of transmission line (TL) faults [1]. Through a machine learning-based technique, they examined both fault resistance and fluctuation of angle owing to fault. U. J. Minnaar et al. (2016) used Wave Form monitoring to investigate the underlying causes of several kinds of problems [2]. They offer an automated technique for this analysis and use symmetrical components of transient and steady-state situations. L. Jing et al. (2018) proposed a method for identifying TL impedance and shunt conductance problems. It outlines a technique for reconstructing the spatial profiles of TL characteristics such as distributed impedance and shunt conductance, from which the existence and position of faults may be detected using an inverse scattering methodology. It gives a distinct mathematical formulation of the spatial profiles of the TL parameters based on Zakharov-Shabat equations. R. Godse et al. (2020) proposed a feature extraction approach based on mathematical morphology for the identification and classification of power TL faults [4]. The literature provides a Fault feature extraction approach based on real-time rapid mathematical morphology. The collected characteristics are then provided as a set of inputs to a decision tree classifier for fault identification and classification. The graphical and numerical outcomes of the retrieved characteristics validate the scheme's capability with accuracy while reducing computational complexity.

M. Z. Fortes et al. (2015) offered numerous ways in their literature to deal with the large number of TL faults applications that are important from a technical and economic standpoint for system operators and owners. The literature discusses TL defect diagnostics, techniques, and their link to applications. H. Tang et al. (2011) used an inverse scattering technique to identify soft flaws in TL with loss [6]. They developed an inverse algorithm to diagnose the continuous spatial changes in reflection and transmission coefficients observed at the TL's ends. The literature explains and completes the calculation of theoretic scattering data needed by the inverse scattering transform from engineering scattering data obtained from the TL.

K. Xia et al. (2020) propose a real-time monitoring system for photovoltaic (PV) production based on ZigBee and 4G Communications [7]. They presented a method for integrating with cloud servers using the Internet of Things (IoT) and remote monitoring of centralised or distributed PV systems using terminal apps. The suggested system implements ZigBee network connectivity and uploads data to the cloud server through communication network utilising 4G network. The three-phase current characteristics are chosen by the server by combining the wavelet packet energy and the waveform parameter. A defect diagnostic model based on a probabilistic neural network is being developed to assess the health of the PV inverter. The benefits are that it needs a low sample frequency and lowers the cost of local devices by putting diagnostics online on the server-side. The supervisor may query and save system information through mobile devices and computer-side web with remote control.

A. K. Al Mhdawi et al. (2020) developed a smart optimization approach for problem diagnostics in the electrical grid utilising a Distributed Software-Defined IoT system [8]. One of the key concerns in TL is power outages in local regions caused by chronic faults in distribution transformers (DTs) owing to a lack of monitoring and frequent maintenance, which reduces grid system resilience. They suggested a software-defined networking (SDN)-based remote IoT monitoring and failure prediction system. The local SDN-sense enables dependable communication capable of providing and forecasting real-time health monitoring indicators.

J. F. Adami et al. (2009) proposed innovative ways to increase the dependability of high-voltage transmission lines [9]. This paper proposed a remote end defect detection and identification system for TL, which allows for the removal or reduction of power utility maintenance procedures. The approach includes a data collecting device capable of recording and storing high frequency signals contained in the TLs, which are then handled and recognised using signal processing methods such as digital filters and neural networks. After defining the pattern of faults using various fault-simulating tests, an algorithm capable of recognising any probable TL fault was built. K. M. Silva et al. (2006) proposed a system for detecting and classifying faults in transmission lines based on wavelet transform and ANN [10]. They suggested utilising oscillographic data to identify and classify TL faults. Based on the fault detection and clearance time acquired from the waveform analysis of current in the time and wavelet domains, a set of rules has been developed. An artificial neural network detects and diagnoses the defect using time domain pattern recognition of voltage and current waveforms.

P. Jafarian et al. (2010) suggested a strong high-speed traveling-wave-based approach for TL power protection [11]. The approach use principal component analysis to determine the prominent patterns in a wavelet-processed data. The distinction between techniques is presented by the protection algorithm based on the polarity, magnitude, and time gap between the travelling waves at the relay station. Z. He et al. (2010) used fault transients to develop a new approach for fault detection and classification in ultra-high voltage TL [12]. A approach that combines the benefits of the wavelet transform, exceptional value decomposition, and shanon entropy. WSE-based fault detection and classification is feasible and has significant practical application potential. H. Livani et al. (2014) developed a novel relaying approach that avoids short comins by introducing a digital impedance protection technology and TLs [13]. A wavelet-based artificial neural network uses a subset of local current from one end of a protected line to categorise the transient value on the neighbouring line. The local current subset comprised of the two aerial modes of the local current. To extract the high frequency component of the current, the discrete wavelet transform (DWT) is applied. [5] emphasized that people who are visually impaired have a hard time navigating their surroundings, recognizing objects, and avoiding hazards on their own since they do not know what is going on in their immediate surroundings. We have devised a new method of delivering assistance to people who are blind in their quest to improve their vision.

F. B. Costa et al. (2014) offered a wavelet-based technique as a suitable alternative for real-time fault identification, although this method often fails to identify faults with over clamped transients and in real-time analysis. DWT is utilised for wavelet co-efficient energy, which has also been employed for defect identification and the presentation of wavelet co-efficient analysis. The suggested energy analysis's performance is unaffected by the mother wavelet, resulting in no time delay in real-time problem identification. L. De Andrade et al. (2014) provide a review of the travelling wave fault finding approach in transmission lines. The incentives technique demonstrates the benefits and drawbacks. The most typical approach for conveying out true defect in transmission line characteristics. The goal of simulating the use of skewness-based discrete wavelet transform to identify distinct voltage signals from different percentages of sag has been accomplished. A positive result must be obtained using this skewness approach in order to address the voltage sag in power quality analysis, which may be valuable in real-time systems.

According to S. Kamble et al. (2014), the most important approach is to identify faults in power quality as a vital resource that can be used to both industrial and commercial clients. It is very difficult to discover and characterise electrical abnormalities that might lead to power quality issues. Wavelet transform analysis, especially the discrete wavelet transform, may identify power quality issues such as voltage sag, swell, transient, and harmonics. These breakdown signals are utilised

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to extract characteristics by performing a variety of mathematical operations such as peak, variation, and skewness.

According to S. Devi et al. (2016), electric power systems are highly significant due to the high demand for electric energy, and as a consequence, power transmission lines have been quickly built. When a disturbance occurs in a transmission line, it may disrupt supplies across a large region. This line necessitates good defence. In transmission lines, the discrete wavelet transform approach is utilised to identify faults. Wavelet transform may identify faults such as line to line, line to ground, double line to ground, and three phase faults. J. N. Chavan et al. (2022) proposed that the transmission line includes multiple strategies for relay protection. The artificial network system was kept in single phase first order in the case of transmission lines. If a transmission line is present in a parallel system, the network's error correction is enabled if the scheme was approved. This combination approach is connected to error correction, and in a neural network system, defect identification is conceivable in the case of a single line circuit. As a result, the current study is related to the detection of faults in transmission lines using wavelets and an artificial network. H. Livani et al. (2014) proposed a hybrid transmission line fault location approach based on machine learning and wavelet analysis. They suggested a technique for hybrid transmission line fault location using a single-ended travelling wave. A combination of an overhead transmission line and an underground wire. DWT is used to monitor transient voltage information. Support vector machine (SVM) classifiers are employed to identify the faulty-section, and the wavelet coefficients of the aerial mode voltages are utilised to localise the problem.

a. Motivation and Aim: While much work has been done for fault detection, as stated in the preceding literature assessment, there are relatively few works that deal with the identification of fault site in a network that spans great distances from Remote End Monitoring (REM). This has prompted the authors to try to locate the fault site of a Radial system that spans vast distances and has two load zones using a method that can be implemented in REM.

b. Work Flow: Following a short literature review in this introductory part, network modelling and specifications are provided in *Section 2*. *Section 3* presents simulated findings in terms of RMS values for normal and fault circumstances. *Section 4* discussed wavelet decomposition-based feature extraction. In *Section 5*, an approach for identifying the fault site for REM is presented, followed by a conclusion in *Section 6*.

2. NETWORK MODELLING AND SPECIFICATION

A long-distance radial network has been explored in this case, as shown by a single line diagram in *figure 1*. It starts with a single source and two load regions are linked by peripheral buses. It is made up of many transmission lines of varying lengths. A grid (U1), five step-down two-winding transformers (T1, T2, T3, T4, and T5), seven bus bars (Bus 7, Bus 2, Bus 3, Bus 4, Bus 5, Bus 6, and Bus 8), five transmission line cables (cable2, cable4, cable5, cable6, cable7), two lump loads (Lump1 and Lump 2), and two motor loads are depicted in the diagram (Mtr1, and Mtr2). The network's exact specs are shown in *table I*.

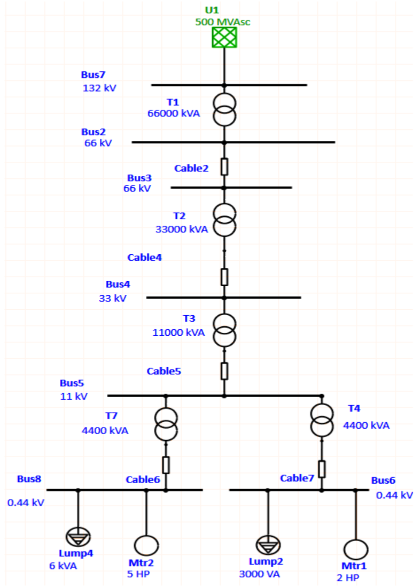

Figure 1: Radial network model

Table 1: Specifications of the network in Figure 1

Sl. No.	Device Name	Quantity	Specification
1	Grid	1	1. U1-500MVAsc
2	Transformer	5	1. T1- 66000kVA 2. T2- 33000kVA 3. T3- 11000kVA 4. T4- 4400kVA 5. T5- 4400kVA
3	Bus	7	1. BUS7- 132KV 2. BUS2- 66KV 3. BUS3- 66KV 4. BUS4- 33KV 5. BUS5- 11KV 6. BUS6- 440V 7. BUS8- 440V
4	Cable	5	1. Cable2- 80Km 2. Cable4-60Km 3. Cable5-20Km 4. Cable6-5Km 5. Cable7-5Km
5	Motor Load	2	1. Mtr1- 2HP 2. Mtr2- 5HP
6	Lump Load	2	1. Lump2- 3KVA

3. SIMULATED RESULTS AT NORMAL AND FAULT CONDITIONS IN TERMS OF RMS VALUE

The radial energy distribution network model shown in *figure 1* was simulated using the Electrical Transient Analyzer Program (ETAP) under normal and three-phase fault circumstances to

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get current ratings in all buses when a fault occurred at a specific bus.

In this instance, seven distinct situations were considered, namely Normal, C1 represents a three-phase fault at Bus 2 near the source, C2 represents the same type of fault at Bus 3 located 80 kilometers from the source, C3 represents a fault at Bus 4 located 140 kilometers from the source, C4 represents a fault at Bus 5 located 160 kilometers from the source, C5 represents a fault at Bus 6 located 165 kilometers from the source, and C6 represents a fault at Bus 8 located 165 kilometers from the source.

In *figure 2*, a bar chart plotted with respect to the buses compares various currents during normal and three-phase fault circumstances that occurred at different buses. The vertical axis displays the current at various buses (for example, I Bus7 indicates the current ratings in Bus 7 during normal circumstances and three phase faults at Bus 7, Bus 2, Bus 3, Bus 4, and Bus 6, Bus 8) while the horizontal axis displays the current rating in kA.

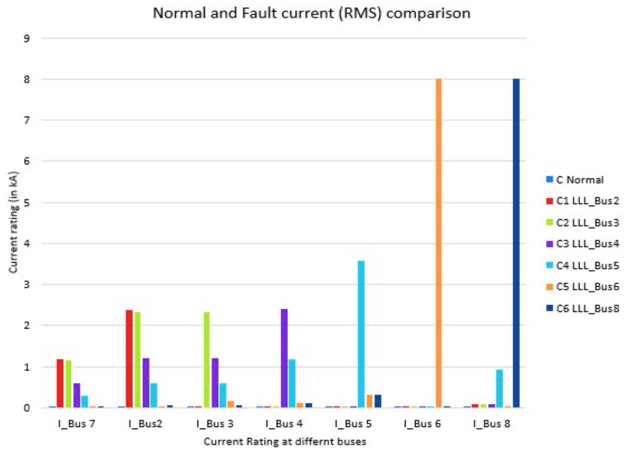

Figure 2: Comparison of RMS fault currents for fault in different buses

4. WAVELET DECOMPOSITION-BASED FEATURE EXTRACTION

Figures 3 and *4* demonstrate the three-phase transient short circuit fault current waveforms for various phases at bus 6 and bus 8. It has been displayed using the transient time period data from a three-phase transient short circuit study at bus6 and bus8.

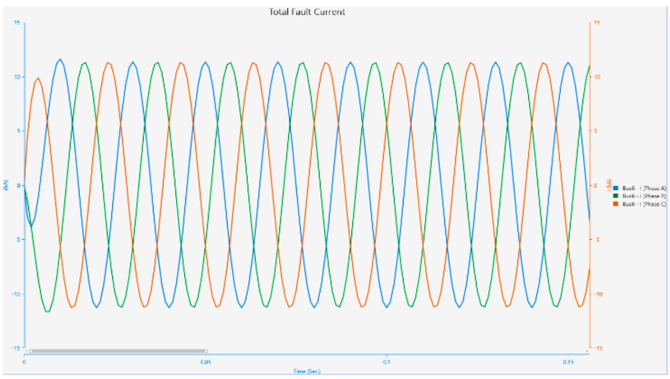

Figure 3: Transient short circuit fault on Bus 6

The wavelet decomposition approach was used to handle the current per phase values at various transient time periods in MATLAB programming. The wavelet function 'db-4' was utilised for decomposition. All signals were decomposed into nine levels, and detailed coefficients were derived at each level of decomposition. The statistical quality of the huge number of coefficients obtained at various levels was appraised by their Kurtosis and Skewness values.

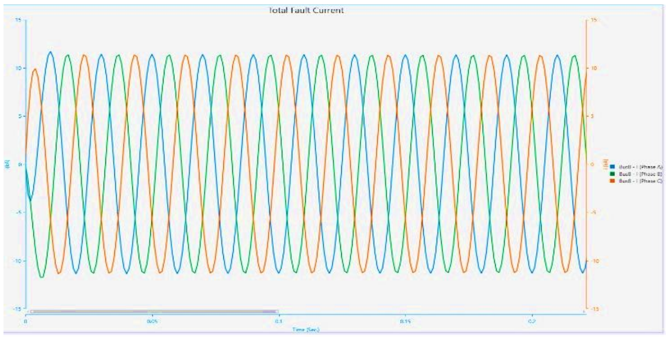

Figure 4: Transient short circuit fault on Bus 8

4.1 Feature Extracted from Kurtosis Data

Kurtosis was determined from the breakdown of the waveform of fault currents for all six examples of faults that occurred at six separate sites. The results are shown in *figure 5* for phase A, *figure 6* for phase B, and *figure 7* for phase C. According to these numbers, there is a sharp increase in Kurtosis from level 4 to level 5. It hits its apex at level 5, and then plummets dramatically at level 6. It demonstrates that the extracted characteristic of Kurtosis is comparable for data belonging to phases A, B, and C, respectively. However, at levels 1 and 5, each phase displays modest variations in Kurtosis values for distinct instances. [3] discussed about a system, a low power area reduced and speed improved serial type daisy chain memory register also known as shift Register is proposed by using modified clock generator circuit and SSASPL (Static differential Sense Amplifier based Shared Pulsed Latch). This latch-based shift register consumes low area and low power than other latches. There is a modified complementary pass logic based 4-bit clock pulse generator with low power and low area is proposed that generates small clock pulses with small pulse width.

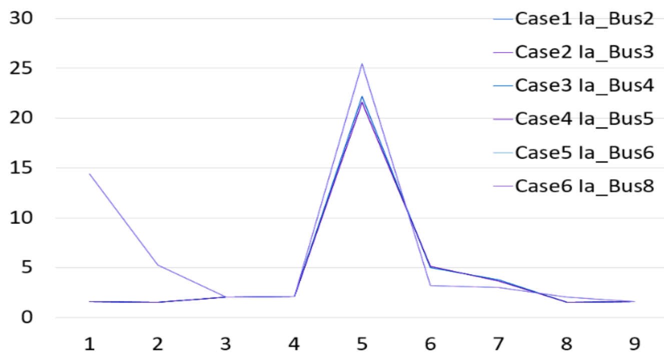

Figure 5: Kurtosis at Phase A for different fault cases

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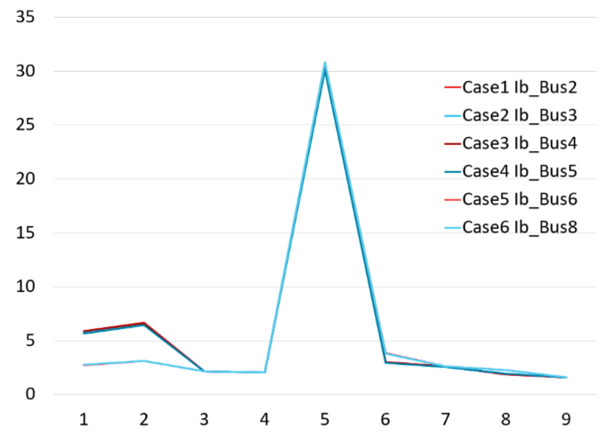

Figure 6: Kurtosis at Phase B for different fault cases

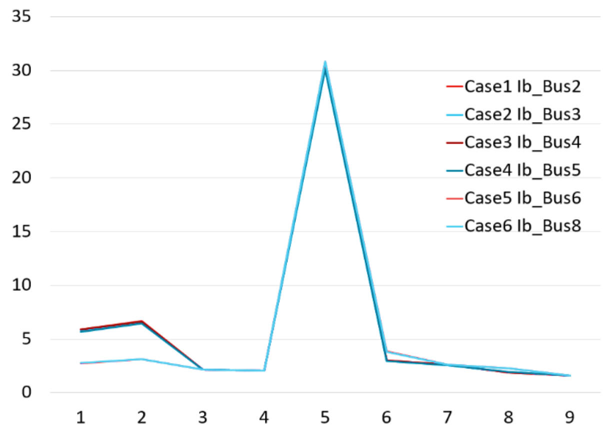

Figure 7: Kurtosis at Phase C for different fault cases

4.2 Feature Extracted from Skewness Data

Skewness was computed from the breakdown of the waveform of fault currents for all six examples of faults that occurred at six separate sites. The result is shown in Fig. *Figure 8* depicts phase A. *Figure 9* for phase B and *figure 10* for phase C According to these numbers, there is a sharp increase in Skewness from level 4 to level 5. It reaches its peak at level 5, and then drops precipitously at level 6 for phase A. At level 5, phase B and C display the inverse, i.e., a negative peak. Interestingly, the Skewness values for various scenarios are varied, as seen in *figure 11* for A phase.

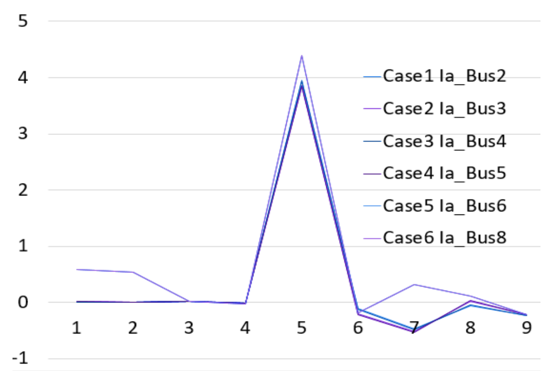

Figure 8: Skewness at Phase A for different fault cases

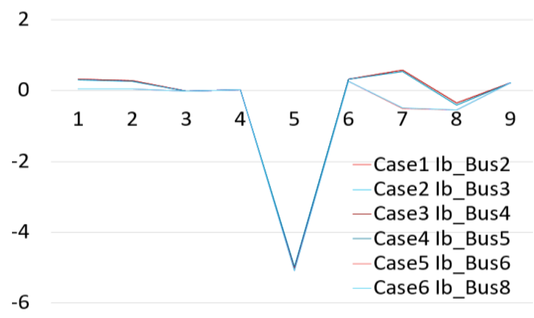

Figure 9: Skewness at Phase B for different fault cases

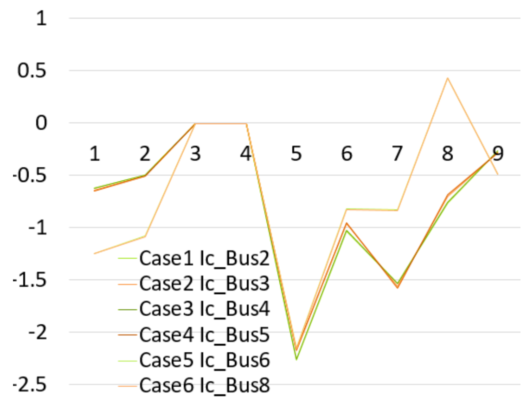

Figure 10: Skewness at Phase C for different fault cases

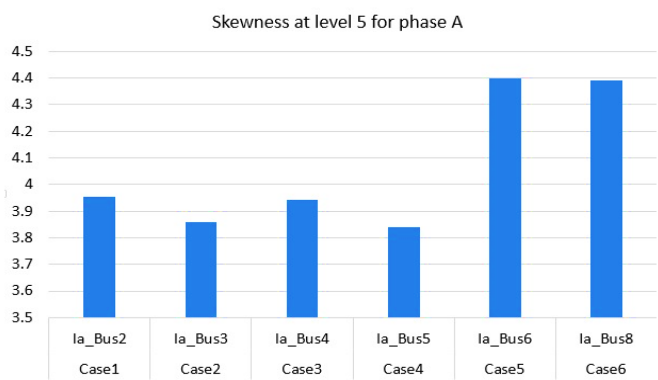

Figure 11: Skewness at level 5 for phase A for different fault cases

5. FAULT DISCRIMINATION USING A MCHINE LEARNING-BASED APPROACH

Following wavelet-based fault discrimination, six alternative machine learning-based algorithms were utilized extract characteristics from fault current time series data. Logistic Regression, Support Vector Machine, K-Nearest Neighbor (KNN), Decision Tree, Random Forest, and Gaussian-Naive Bayes were the algorithms employed to classify six fault scenarios. All algorithms were initially run via a large quantity of known time series data. They were then evaluated using unknown data with varying degrees of unpredictability. The results with 10% randomness are displayed in *figure 12*. As shown in *figure 1*, % accuracies were calculated for various percentages of randomness using different techniques. 13. It

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demonstrates that Decision Tree is very accurate in the majority of circumstances.

6. CONCLUSION

This work presents wavelet and machine learning-based approaches for the discrimination of different faults that occurred at different locations in a radial power distribution network. Fault currents were analyzed through wavelet decomposition-based detail coefficients and by their Kurtosis and statistical nature. Level 5 of Skewness shows different magnitudes for different fault cases. However, for better fault discrimination, six different machine learning-based methods were used and then tested with random unknown data in time series. The decision tree method was found best giving the highest accuracy in most of the cases. This approach may also be used for other type of fault discrimination and in other types of distribution networks.

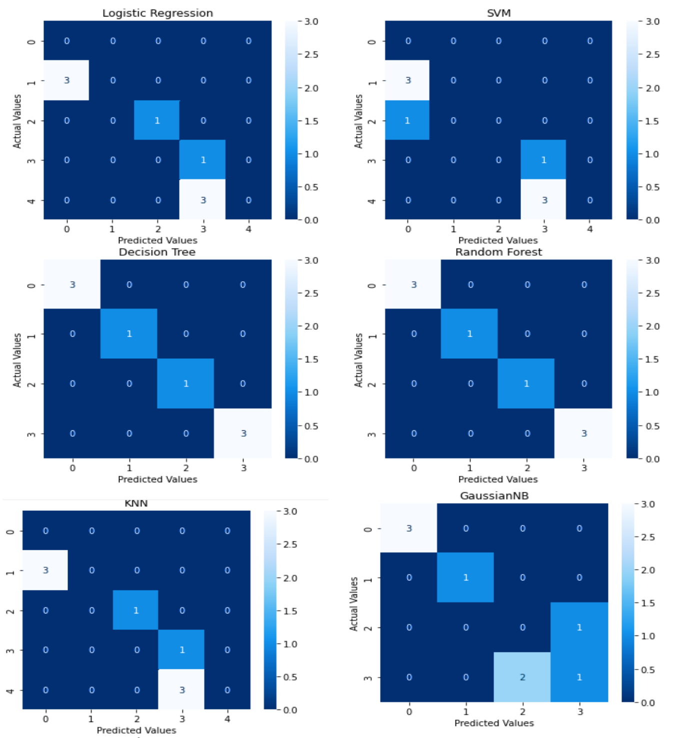

Figure 12: Machine learning-based outcomes with unknown data having 10%

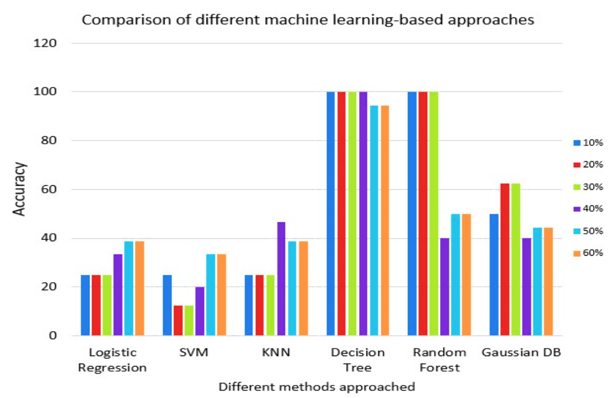

Figure 13: Percentage accuracies for different percentages of randomness using different algorithms

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