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Power Transmission Line Fault Detection and Classification Using Feature Extraction

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ABSTRACT

Transmission lines are critical components of power systems, responsible for delivering electricity over long distances. Faults in transmission lines such as short circuits, open circuits, or ground faults can lead to severe disruptions, equipment damage, and power outages. Timely and accurate detection and classification of these faults are essential for maintaining the stability and reliability of the power grid. This work presents a fault detection and classification in transmission lines using advanced signal processing techniques and machine learning algorithms. The proposed system analyzes current and voltage signals captured at the sending and receiving ends of the transmission line, extracts relevant features, and classifies fault types including single line-to-ground (SLG), line-to-line (LL), double line-to-ground (DLG), and three-phase faults. Simulation models are developed in MATLAB/Simulink to evaluate system performance under various fault scenarios and noise conditions. The results demonstrate high accuracy in both detection and classification.

The DWT transform decomposes the current signal at 5 detailed level and the energy of current signal is calculated and fed as an input to machine learning for fault classification.

Keywords: Transmission line faults, DWT, Machine learning, KNN, Confusion matrix, etc.

1. INTRODUCTION

A transmission line is an essential component of the electrical power system, carrying electrical energy from power plants to distribution substations and, eventually, to customers. The transmission system is comparable to the arteries in the human body. Transmission lines generally transport bulk electrical power from centralised power generation units (such as hydroelectric plants, coal-fired power plants, nuclear power plants, or renewable energy sources) to diverse areas and cities where electricity is used. Transmission systems operate at high voltages to minimise energy loss, as electricity travels from generation points to regional substations. The system's efficiency and reliability depend on advanced technologies and infrastructure to maintain a stable power supply while reducing environmental impact.

2. REVIEW OF LITERATURE

Sheng Su et al [1] discussed the Electromagnetic Transient Program (EMTP), Power System Computer-Aided Design (PSCAD), the real-time digital simulator (RTDS), and the artificial neural network (ANN) for fault classification in transmission lines. Based on detailed observation and investigation of the ATP's functioning mechanism. M. M. Eissa et al.[2] introduced a protection scheme depending on compares positive sequence voltage magnitudes for specified areas and positive sequence current phase difference angles for each interconnected line between two areas on the network. Jiuwen Cao et al. [3] presented experimental results on the regression of some nonlinear functions and real-world data, the prediction of a chaotic signal and classifications on serval benchmark real-world data sets show that the proposed neural networks can achieve better performances in most cases than some relevant neural networks and learn much faster than neural networks training with the traditional back-propagation (BP) algorithm. N. Perera, et al. [4] investigated the applicability of the decision tree, hidden Markov model, and probabilistic neural network (PNN).

3. FAULTS IN TRANSMISSION LINE

Faults in transmission lines can develop at any point along the line, preventing it from performing its intended purpose. Identifying transmission line faults in a short duration is essential to maintain the reliability of the power system. The following table 1.1. Shows the possibility of faults in different areas of the power system.

Table 1. Possibility of Faults in Power System

Equipment	Percentage %
OH lines	50
Cables	10
Transformers	9-12

Switchgear	13-15
Control equipment	2-3
Instrument Transformer (CTs and PTs)	1-2

The table above clearly illustrates that the possibility of problems on transmission lines is much higher than other equipment of the power system.

4. FEATURE EXTRACTION TECHNIQUES WAVELET TRANSFORM

A mathematical method for processing and analyzing signals or data at various sizes or resolutions is the wavelet transform. It is very helpful in time-frequency analysis, image compression, and signal processing. A sampled version of the CWT with discrete scale and translation parameters is called the Discrete Wavelet Transform. It is defined as.

$Wx(j,k)=\Sigma x(n).\Psi j,k(t)\ \infty n=-\infty dt$ ---- (1)

Where: j is the scale (or level), k is the translation (or shift), x(n) is the input signal, Ψ(t) is the mother wavelet

The DWT analyses the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detailed information. DWT employs two sets of functions, called scaling functions and wavelet functions. Which are associated with low-pass and high-pass filters, respectively.

5. SYSTEM STUDIED

The IEEE 9-bus system is a popular benchmark for testing transmission line fault classification algorithms in power system research. This test system, which consists of 9 buses, 3 generators, and 9 transmission lines, provides a realistic model for modelling various fault situations, including line-to-line, line-to-ground, and three-phase failures. The IEEE bus system is developed in MATLAB simulation, and various faults are created at multiple bus locations. of the classifiers is analyzed by using the various methods. Including Parallel coordinates. The following Figure 1 shows IEEE 9 bus system.

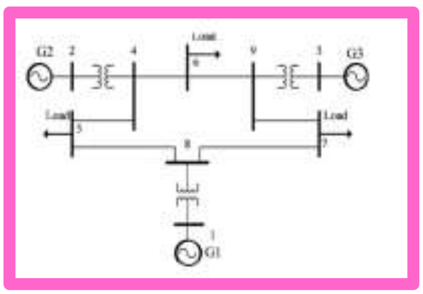

Fig-1 IEEE 9 bus system

Different types of faultshave been created on various buses. the following figures 2 show the waveforms of LG fault Current signal of transmission line bus 7-8 at 200 KM distance.

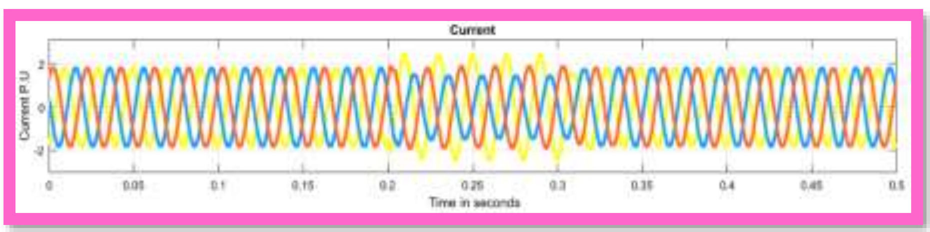

Fig-2 LG fault Current signal of transmission line bus 7-8

Also, the LL fault Current signal of transmission line bus 7-8 is shown in Figure 3

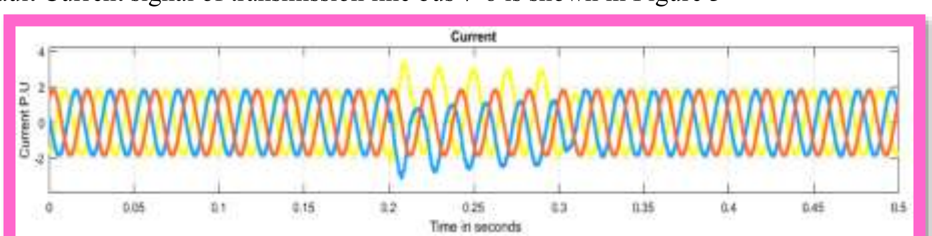

Fig-3 LL fault Current signal of transmission line bus 7-8

Similarly, LLG and LLL faults were created on IEEE 9 on the buses 7-8, 6-9, 5-7,8-9, 9-3,4-5,4-6, 4-1 and bus 2-7.and the current and voltage of the faults have been captured

6. PROPOSED METHODOLOGY

Wavelet Classification Learner Application method requires the following steps.
The step-by-step procedure of this algorithm is given below.

1. Simulation IEEE 9 bus Test system in MATLAB Simulink.
2. Symmetrical and unsymmetrical faults such as L-G, L-L, L-L-G, and LLL types are generated on buses 7-8, 6-9, 5-7,8-9, 9-3,4-5,4-6, 4-1 and bus 2-7.
3. Captured fault current and voltage signals of transmission lines with a duration of 0.5 sec at 10 kHz sampling frequency.
4. Output files of the Simulation are converted into Excel sheets.
5. Excel sheet data is imported into the MATLAB program for DWT analysis.
6. Discrete Wavelet Transform is applied to current signals and decomposed up to 5 levels.
7. The Energy of the signal can be calculated as $E = \sum_{n=0}^{N-1} = |x(n^2)|$

Where, n= no. of samples, x(n) is the discrete signal

8. The Excel sheet data is prepared.
9. This sheet is given as input to the Learner application for Symmetrical and Unsymmetrical faults.

The wavelet MATLAB learner approach records the fault current and voltage of various faults, calculates the energy of the current signal, and uses these samples input to the MATLAB learner application. With the help of 22 different Algorithms

7. WAVELET TRANSFORM BASED CLASSIFICATION

This work shows the signatures of various faults obtained by calculating the DWT of current signals up to detail level 5. The sampling frequency is 10 KHZ, and this study is performed for 0.5 cycles. Hence, all the line current signals contain 5000 samples. The samples are reduced at each detail level, i.e. level d1 includes 2500 samples, level d2 contains 1200 samples, level d3 contains 600 samples, level d4 contains 300 samples, and level d5 includes 150 samples. As the DWT level increases, more detailed information is extracted from the signal. The Db5 Wavelet is used for the decomposition of signals.

7.1 Bus 7-8 Results of Wavelet

The following figures 4 shows the wavelet results for the various types of faults. The graphs show the relationship between the samples (x-axis) and the magnitude of the current (y-axis).

1. Bus 7-8 wavelet transform for L-G fault at a 200km

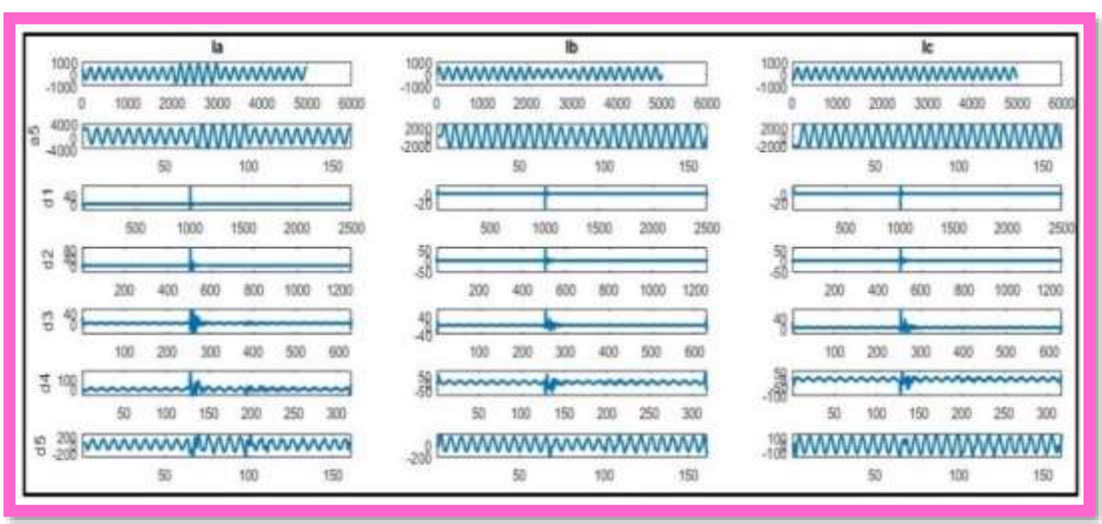

Fig-4 DWT waveform of current signal for L-G Bus 7-8

In this case, the Line to ground fault is on phase a so the energy of fault current phase a increases as compared to phases b and c. The energy levels increase from d1 to d5 level. The d5 level energy has a high energy coefficient.

2. Bus 7-8 wavelet transform for L-L fault at a 200km

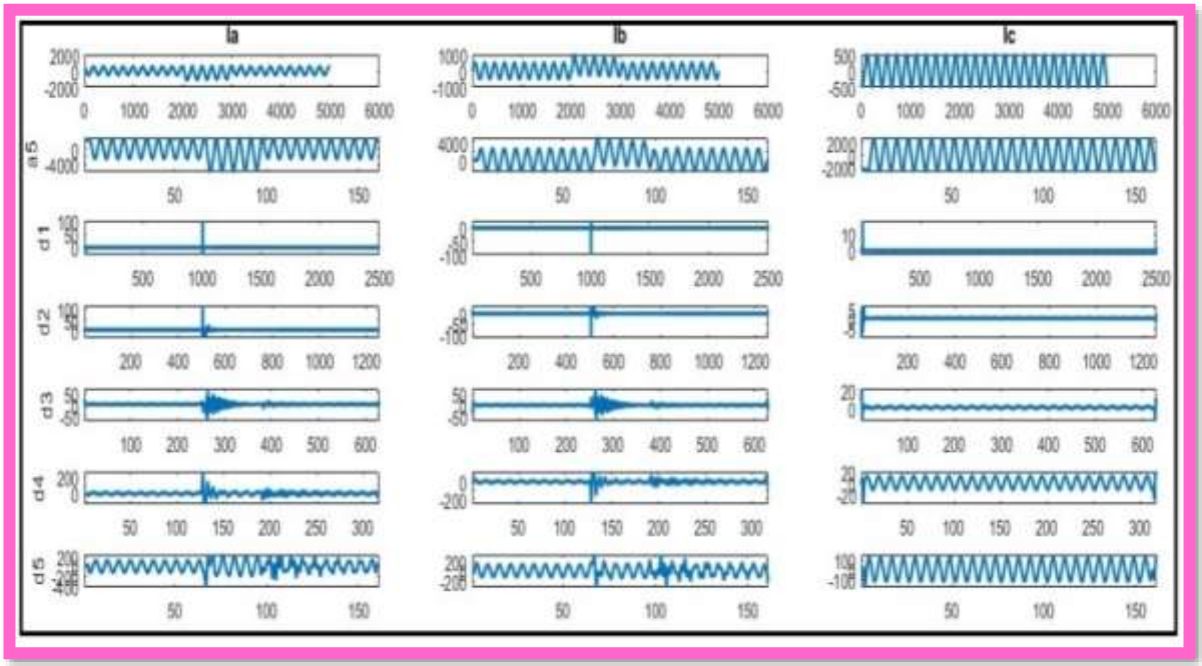

Fig -5 DWT waveform of current signal for L-L Bus 7-8

In this case, the Line-to-Line fault is between phases a and b, so the energy of fault current phases a and b increases as compared to phases c. From the d1 level to the d5 level, the energy levels rise. The energy coefficient of the d5 level is large. The energy samples of buses 7-8 for various types of faults have been tabulated in the following Table 1. Similarly, wavelet transform of the different fault current of buses 7-8, 6-9, 5-7,8-9, 9-3,4-5,4-6, 4-1, and bus 2-7 and its energy have been calculated.

Table 1 Energy samples for bus 7-8 using wavelet transform

L-G 7-8	L-L 7-8	L-L-G 7-8	L-L-L 7-8
0.100952	1.71E-01	2.08E-01	4.68E-01
0.15106	3.46E-01	0.372788	0.984613
0.3599	1.12E+00	1.13E+00	3.16E+00
1.757396	2.89E+00	2.94E+00	5.82E+00
26.49896	2.70E+01	2.89E+01	3.01E+01
0.027756	1.60E-01	1.31E-01	1.65E-02
0.09489	3.47E-01	3.40E-01	4.21E-02
0.170924	1.16E+00	1.23E+00	2.23E-01
1.034488	2.88E+00	2.51E+00	1.33E+00
18.84624	2.46E+01	2.59E+01	2.43E+01
0.033787	7.68E-03	1.75E-02	3.14E-01
0.092046	5.46E-03	3.92E-02	6.71E-01
0.128854	2.34E-02	7.60E-02	2.17E+00
0.943532	3.92E-01	7.31E-01	3.56E+00
20.49876	1.97E+01	1.87E+01	2.80E+01

The classification of the faults is 100% by using the KNN classifier is obtained with the 7-fold and 30 per cent holdout validation it is a try-and-error method; the folds and holdout percentage need to be changed to obtain high classification accuracy. the 100 percent classification is obtained using KNN fine classifier.

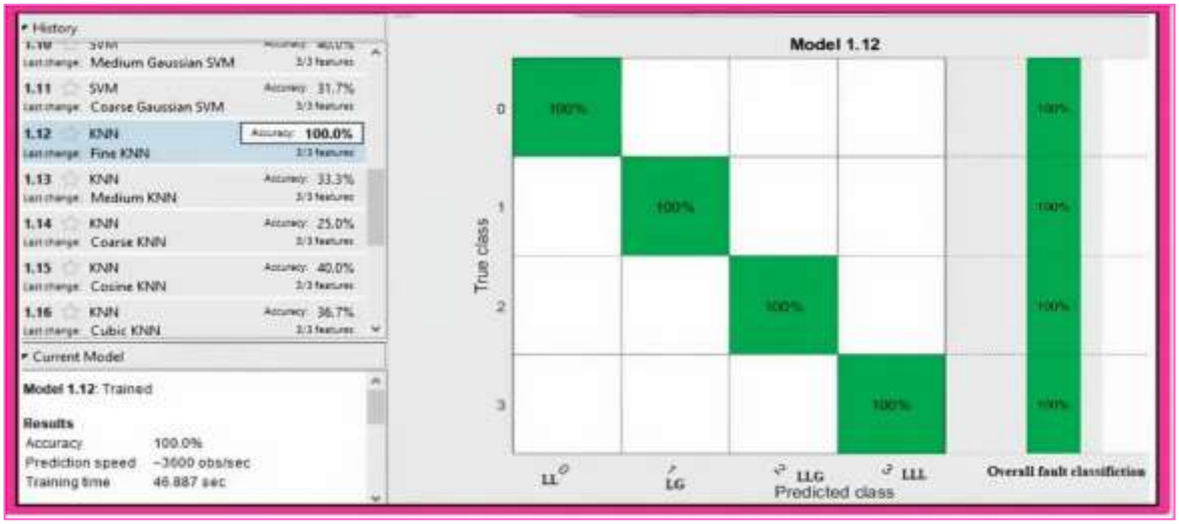

Fig-6 Confusion matrix of KNN classifier

Other KNN classifiers, such as Medium KNN, show 33 per cent classification accuracy, coarse KNN gives 25 per cent accuracy, Cosine KNN gives 40 per cent classification accuracy, and cubic KNN gives 36.7 per cent classification accuracy. The confusion matrix is shown in Figure 6.

8.CONCLUSIONS

Power transmission line fault detection and classification are essential for ensuring the stability, dependability, and safety of electric power systems. Transmission line defects, such as short circuits, grounding difficulties, or line-to-line faults, can impede power flow, damage equipment, and result in costly outages. Rapid identification and exact classification of these failures allow operators to isolate impacted areas, reduce downtime, and restore service more effectively.

This work presents a novel approach for classifying faults on high-voltage transmission lines. The IEEE 9 bus system is simulated using MATLAB Simulink block line. currents and voltages are utilised to extract discriminating characteristics from DWT, which possesses an intrinsic temporal frequency localisation property. 100 per cent of transmission line fault classifications were obtained from Wavelet and Machine Learner applications. The K nearest neighbour (KNN) gives a 100 per cent classification result.

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