

Deep Learning Based Identification and Categorization of Transmission Line Fault

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Abstract: Fast and accurate fault identification is instrumental in the reliable functioning of power transmission systems. When done promptly, it can significantly limit the damages to equipment as well as power interruptions. Typically, Identification and categorization of faults Techniques are founded on mathematical models and threshold operations. However, these methods experience difficulties when dealing with varying system conditions, noise, and non-linear behavior. This study introduces a deep learning based solution to the problem of the identification and classification of transmission line faults. The approach involves gathering voltage and current signals from transmission lines under both ideal and flawed circumstances. The signals are then reprocessed and fed into They are trained using deep learning models like Long Short Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). These models are capable of automatically extracting the most relevant features from the time, domain and frequency, domain representations of the signals, thereby obviating the need for manual feature engineering. The developed network can not only locate a fault but also identify its category, For instance, single line, to, ground, double line, to, ground, and three-phase faults. Simulation studies conducted under varying fault locations, fault resistances, and noise levels demonstrate that the proposed deep learning framework achieves high accuracy, robustness, and faster response compared to conventional methods. The results confirm that deep learning techniques provide an effective and reliable solution for real-time fault identification and categorization in modern power transmission systems.

Keywords: Deep Learning, Transmission Line Faults, Fault Identification, Fault Classification, Signal Processing, Power System Protection, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN)

1. Introduction

A connection between several sources and loads is known as the electric power transmission network. It is the most crucial component of the nation's energy infrastructure. As the nation grows, more dispersed distribution sources and electrical loads are added to the current power network due to the rising demand for electricity. As a result of the disturbance or fault, particularly the electrical fault, complexity is rising across the electrical system. Weather, neglected operations, overload, equipment malfunctions, human error, and fire smoke are the sources of fault. In recent decades, technological, human, and electrical faults have caused significant blackouts in the power systems. Overcurrent flow, personal risk, equipment loss, financial loss, and national security are the consequences of them. Artificial Neural Networks (ANN), Fuzzy Logic (FL), Convolutional Neural Networks (CNN), and Gate Recurrent Units (GRU) are some of the techniques used to address Single Line to Ground (SLG), Line to Line (LL), Double Line to Ground (LLG), and Threeline (LLL) and Three-Line to Ground (LLLG) faults. Due to the intricacy of the fault modeling on various fault types the creation of a deep learning technique used to identify and classify transmission line faults. Under the fault conditions, this suggested method can recognize and categorize both symmetrical and unsymmetrical faults. In order to identify faults and process energy distribution during transient states, multi-resolution analysis is employed. The sub band signal's energy is transmitted under the feature vector form following feature extraction. It is used as a deep learning algorithm's input to classify fault types.

2. Propose Algorithm

The methodology begins by collecting current and voltage data from all three phases of the electrical system. The signals are the basis for understanding the system behavior. The Wavelet Transform, a complex mathematical tool, is then used to break down the signals. This operation breaks the complex signals down to their simpler components, which in turn exposes their frequency characteristics. Subsequent to the signal decomposition, the attention is directed to the energy feature extraction from the decomposed signals. These features contain the most important information about the signal's energy distribution in different frequency bands. It is like extracting the core from the signals, which energy is spread out within the system then goes on to fault detection with the energy features extracted from the signals. At this point, deviations or abnormalities in the signals are detected, which indicate the presence of faults in the system. This stage is very important because it works as a prediction tool, giving the operators the chance to anticipate the problems before they escalate. Detected faults are examined and characterized according to their differing features. Such classification gives a clear picture of the type and extent of the fault, which in turn will enable the operators to take the right steps to avert the risks and maintain the normal functioning of the electrical system the method is a systematic approach that employs advanced.

3. IEEE 5 Bus System

The depicted circuit configuration is intended for the research and analysis of faults on a transmission line. Two 3, phase sources, each producing 400 kV at 50 Hz, act as main power inputs. These sources feed a very long transmission line, which can be extended up to 500 km. Within the specified time frame of 0.4 to 0.6 seconds, a three-phase fault is intentionally induced along this transmission line for examination. It's notable that the transmission line is not just a linear structure rather, it branches out to three distinct locations as shown in figure 1.1 the fault scenarios and classification model are simulated in the MATLAB/Simulink environment.

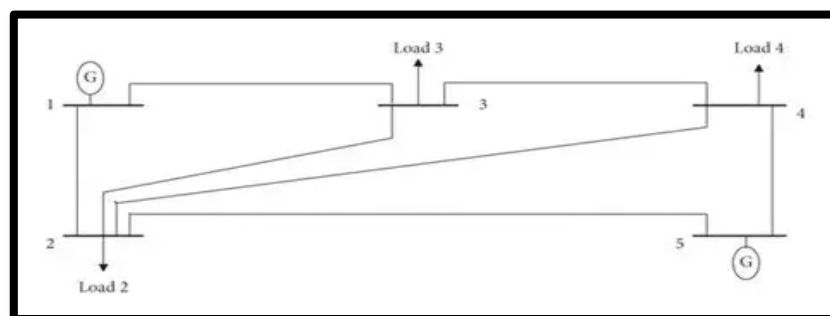


Figure 1.1. Two generator system

3.1. L-G Fault

R-G, Y-G, and B-G faults are the L-G faults that occur in transmission systems. Here, R-G fault is taken into consideration as an example. The voltage and current waveforms of the RG fault system are displayed in figures 2 and 3. Compared to other phases, the R phase signals have more transients.

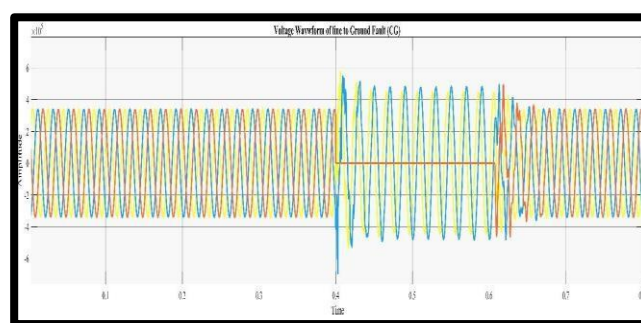


Figure 1.2. L-G Fault (Voltage waveform)

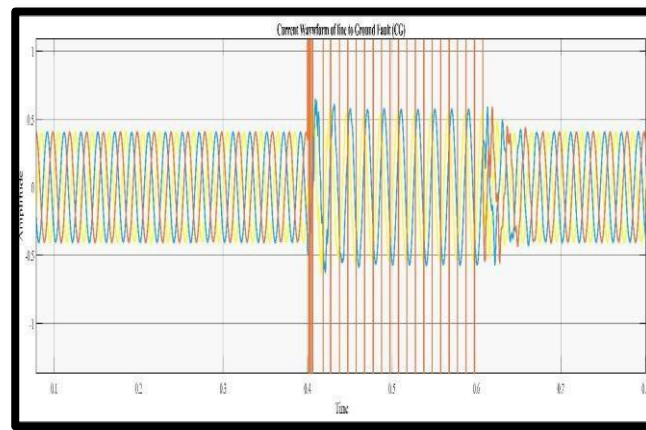


Figure 1.3. L-G Fault (Current Waveform) Similarly, faults including line-to-line (LL), double line-to-ground (DLG), and three-phase (LLL) faults are simulated at different buses and locations within the transmission network.

4. Features Extraction wavelet Transform

The mathematical field of wavelet theory deals with creating a model for non-stationary signals using a collection of elements known as wavelets that resemble tiny waves. Since its launch, it has grown to be a wellknown and practical tool, particularly in signal and image processing. Since the Continuous Wavelet Transform (CWT) is calculated by varying the analysis window's scale, moving the window in time, multiplying the signal, and the information of interest is frequently a combination of features that are well localized temporally or spatially, the DWT is simpler to implement than CWT. This necessitates the adequate application of analysis techniques that are flexible enough to manage signals in terms of their time-frequency localization. Since Fourier's time, frequency-based analysis has been widely used; however, because Fourier-based analysis relies on the non-transient sine and cosine functions, frequency analysis is not the best method for transient analysis. Transients are broken down into a number of wavelet components via the wavelet transform, each of which represents a time domain signal covering a certain octave frequency band with more specific information. These wavelet components seem to be helpful in identifying, locating, and categorizing transitory sources. Thus, utilizing the wavelet transform to evaluate power system transients is both feasible and beneficial. The figure shows the high frequency and low frequency splitting of the transient signal.

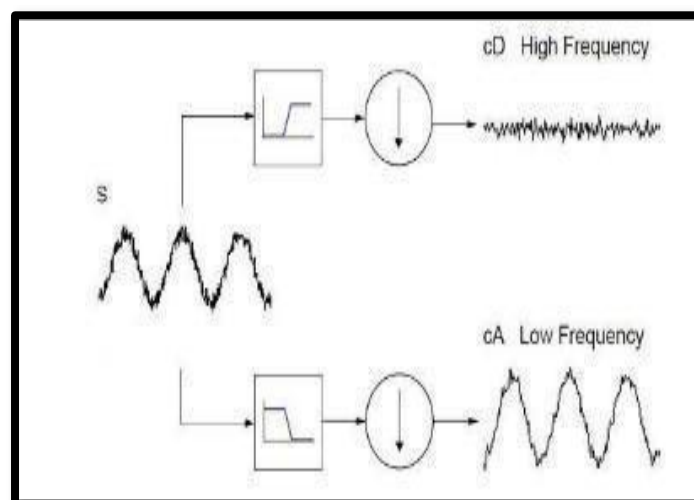


Figure 1.4. Analysis of signal using wavelet transforms

4.1. Wavelet Transform Output

The research exemplifies the application of a transformative tool to dissect and interpret the energy distribution within the electrical system. It systematically expounds the different components of the wavelet output, offering a lucid understanding of its operation and importance in signal processing. Depicting the constituent elements of the wavelet output is, to a great extent, the story of the chapter. The original signal is the basic representation of the raw three, phase current data, thus it depicts the electrical signals in an unaltered manner. Then, the approximate signal is singled out for a coarse, grained approximation of the original data it provides, thus it is instrumental in the identification of the overarching trends and patterns. Moreover, the wavelet decomposition produces a set of detailed energy signals labeled as D1, D2, D3, D4, and D5. These signals, which are said to have varying granularity levels, match the original signal's high-frequency components at various scales. By studying them, one gets a more detailed temporal and spectral view of the electrical signals, which makes it easier to locate transient phenomena and harmonic distortions.

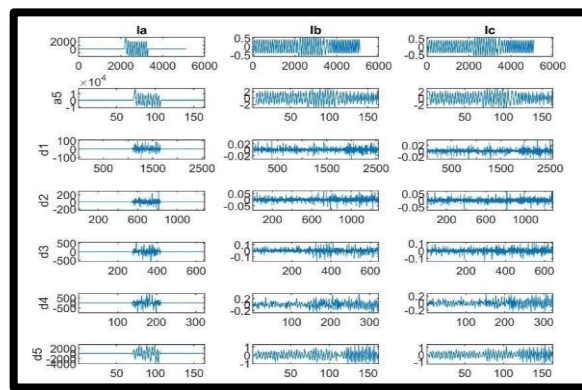


Figure 1.5. The Wavelet Transform AG Fault Result

Scaled and shifted copies of a mother wavelet are used in DWT to assess the signal. The discrete wavelet transform is defined as follows

$$W(j, k) = \sum x(n) \psi_j, k(n) \quad (1)$$

Where

$x(n)$ = sampled voltage or current signal

$\psi_j, k(n)$ = wavelet function at location k and scale j

j = decomposition level

k = time shift index

The scale and translation parameters are chosen as

$$a = 2^j \quad (2)$$

$$b = k \cdot 2^j \quad (3)$$

The original signal goes through the Low-pass filter to get the Approximation coefficients (A) and the High-pass filter to get the Detail coefficients (D).

$$\text{So, } x(n) = A_j(n) + D_j(n) \quad (4)$$

The Detail coefficients contain high-frequency components produced due to faults.

The Energy from the decomposed wavelet signal is calculated using

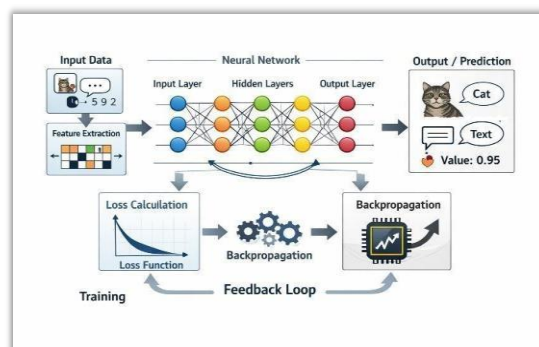
$$E_i = \sum |D_i(n)|^2 \quad (5)$$

Table I Energy samples for Line to ground fault

IA	IB	IC
2.02E+05	0.060439	0.063176
0.10846862	7.72E+05	0.108559
0.09146704	0.094639	1.09E+06
1.65E+06	1.65E+06	0.076945
0.06965917	2.69E+06	2.69E+06
2.03E+06	0.088813	2.03E+06
4.85E+06	6.41E+06	6.55E+06

5. Deep Learning

Artificial neural network architecture is the foundation of the artificial intelligence subfield known as deep learning. Layers of interconnected nodes known as neurons are used by artificial neural networks, or ANNs, to analyze and learn from input data. An input layer and one or more hidden layers connected sequentially make up a fully connected deep neural network. Each neuron gets input from the input layer or neurons in the layer before it. One neuron's output is used as an input by other neurons in the network's subsequent layer. This procedure is repeated until the network's output is produced by the last layer. By applying a number of nonlinear transformations to the input data, the neural network's layers enable it to learn intricate representations of the input data. Supervised, unsupervised, and reinforced machine learning are all possible with deep learning. It processes these in a number of ways. In an attempt to train the model, another method known as back propagation use methods such as gradient descent to compute prediction errors and then modifies the function's weights and biases by going backward through the layers. A neural network can produce predictions and make the required adjustments when forward and back propagation are coupled.



6. Methodology

Choosing Orange software as the main platform for model creation and evaluation is a clear signal of the intention to employ up-to-date instruments in the field of data science and machine learning. Orange, being widely known for its user-friendly interface and powerful features, delivers a full environment suitable for both the discovery and the refinement of predictive models. This versatile tool provides a broad library of machine learning algorithms, which include not only conventional methods like decision trees and support vector machines, but also advanced techniques such as deep learning networks. Besides, Orange's simple-to-use interface permits the smooth integration of these algorithms into the modelling workflow, thus, it is possible to efficiently carry out the experimentation and iteration. While its diverse algorithmic offerings have been highlighted, Orange also performs well in its provision of powerful visualization instruments. These instruments enable users to deepen their understanding of their data and the performance of the model by means of interactive visualizations, such as scatter plots, heat maps, and decision trees. By identifying the most important patterns and relationships in the

data, analysts can take the right steps for feature selection, model parameters, and even overall model interpretation. The deliberate choice of Orange as the main modeling platform is in line with the intent of creating conditions for the analytical work to be performed efficiently and effectively.

6.1. Model Development and Evaluation

At the start of our investigation, we dove deep into the dataset and made good use of the energy signals from phases A, B, and C. We fully understood how crucial it was to choose the best machine learning algorithm for our predictive modeling, so we went through the methodologies with a fine, tooth comb. We experimented with several machine learning algorithms, each of them distinctly innovative in its way of pattern recognition and classification, were put into operation. In this respect, these algorithms embraced logistic regression, stochastic gradient descent, Naive Bayes, support vector machines (SVM), deep neural networks (DNN), k, and nearest neighbors (KNN). Our attention during this repetitive undertaking was centered on the ability of each algorithm to predict faults with the energy signal data accurately. We thus took the dataset through a very thorough performance test, and each algorithm was judged very closely. Had it not been for this painstaking, detailed, and thorough testing procedure, the deep neural network (DNN) might not have been singled out as the best, achieving an outstanding accuracy of 91%. This excellent accomplishment really illustrates how DNNs, are capable of, among other things, finding complex and subtle patterns in the data, thereby giving them the edge over other predictive modelling tools. The uncovered comparative analysis of strengths and weaknesses is just one part of the research narrative

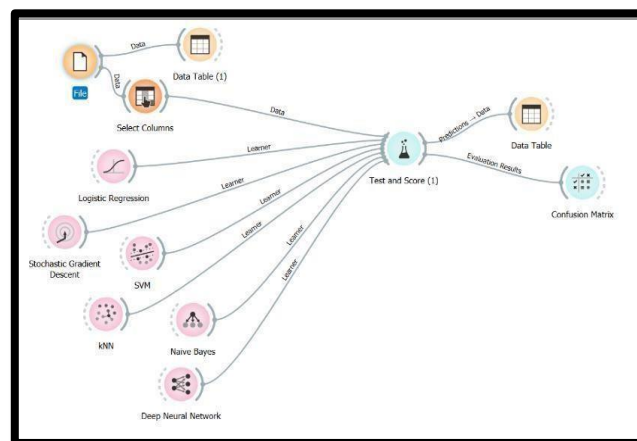


Figure 1.7. Comparative model of different algorithms

Confusion matrix for Naive Bayes (showing proportion of actual)

		Predicted			Σ
		LG	LL	LLL	
Actual	LG	72.7 %	27.3 %	0.0 %	450
	LL	33.6 %	56.7 %	9.8 %	450
	LLL	3.7 %	8.7 %	87.7 %	300
Σ		489	404	307	1,200

Figure 1.8: Confusion matrix for SVM

7. Result and Discussion

The result of using the deep learning algorithm to classify random energy signals into fault categories. The algorithm was trained on a dataset of energy signals recorded during fault conditions, with the aim of accurately locating Fault within the signals. A file of Fault was then generated from the algorithm's predictions.

Model	AUC	CA	F1	Prec	Recall	MCC
Deep Neural Network	0.974	0.917	0.916	0.922	0.917	0.876

Figure 1.9: Accuracy of Classification

The performance of our deep learning algorithm for fault classification is reflected in the evaluation metrics that signal the algorithm's power. The Area under ROC Curve (AUC) reaching a value of 0.974 is indicative of a significant discriminatory ability, thus stressing the algorithm's capacity in differentiating between various fault categories. In the same way, the classification accuracy of 0.917 is a strong signal of the algorithm's capability in assigning the correct fault categories as it is the ratio of correctly classified instances to the total evaluated. Moreover, the precision of 0.922 is a clear indicator that the algorithm was very accurate in reducing false positives, thus precision is the number of correctly classified instances divided by the total instances classified in a specific fault category. In addition to precision, recall of 0.917 confirms that the algorithm has the ability to find all instances in a particular fault category, thus it was very dependable in identifying faults. Together, these metrics serve as a testament to the algorithm's capability and dependability in the execution of fault classification tasks, thus illustrating its possible deployment in the real world where fault detection is a prerequisite for system reliability and maintenance optimization.

		Predicted			Σ
		LG	LL	LLL	
Actual	LG	98.2 %	1.8 %	0.0 %	450
	LL	15.6 %	83.8 %	0.7 %	450
	LLL	0.7 %	5.7 %	93.7 %	300
Σ		514	402	284	1,200

Figure 10: confusion matrix

The confusion matrix depicts the classification results of the deep learning algorithm employed for fault identification. It shows how each actual fault category (row) was classified by the model (column). For example, the cell at row "LL" and column "LL" shows that 83.8% of LL Fault were identified correctly, while the cell at row "LL" and column "LG" shows that 15.6% of LL Fault were wrongly labeled as LG Fault. The "" row and column indicate the total number of instances per category. In sum, the confusion matrix serves as a powerful tool for evaluating the algorithm's accuracy and determining the areas where further enhancement is needed.

Deep Neural Network	error	Ea	Eb	Ec
LG		0.0672448	1.78395e+06	1.76357e+06
LL		0.0696592	2.68703e+06	2.68655e+06
LG		0.0720329	1.86661e+06	1.86626e+06
LG		0.0906874	0.0919918	1.10629e+06
LG		0.091467	0.0946391	1.08879e+06
LG		0.108469	772181	0.108559
LG		0.110162	0.108488	1.2096e+06
LG		0.111174	867293	0.104071
LG		0.112047	862918	0.103717
LL		0.253806	7.85071e+06	7.84904e+06
LG		0.298506	0.312262	2.9969e+06
LL		0.299216	9.66762e+06	9.66514e+06
LG		0.314686	0.295089	3.51894e+06
LL		0.332223	8.6223e+06	8.61993e+06
LG		0.353972	0.353462	3.33403e+06
LG		0.358716	4.07606e+06	0.415388
LG		0.360131	3.38266e+06	0.393388
LG		0.389116	2.97792e+06	0.396119
LG		0.804446	0.874235	6.76476e+06

Figure 11: Data & Predictions Table

Each entry in the sample output data of predictions generated by the deep neural network (DNN) model corresponds to a specific instance or observation in the dataset. The predictions represent the fault category that the model has assigned to each instance. This sample output data is very useful for understanding the working of the DNN model in fault classification from energy signals. The performance of the model can be gauged from the predictions that it generates, in the accuracy of the model, the emergence of patterns or trends in the classifications, and also in the effectiveness of the model in fault identification tasks.

8. Conclusion

The deep learning, based identification and characterization of transmission line faults have shown marked improvements in the accuracy, speed, and reliability of fault detection compared to conventional methods. The proposed approach, by automatically learning complex patterns from electrical signals, allows for precise fault classification and contributes to grid resilience under various operating conditions. While there are challenges related to data dependency, model complexity, and computational requirements, these can be sufficiently

handled by an optimized model design and a robust training strategy. In general, the system proposed is viable for practical implementation and is a significant advancement towards intelligent, adaptive, and reliable power system protection.

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