S-TRANSFORM AND MACHINE LEARNING-BASED IDENTIFICATION AND CLASSIFICATION OF FAULTS ON POWER TRANSMISSION LINES

Prof. Vaibhav A. Ghodeswar and Dr. Mirza Ansar Beg
Department of Electrical Engineering, Mauli Group of Institutions College of Engineering and Technology Shegaon, India
ghodeswarvaibhav@gmail.com and ansarbeg@gmail.com

ABSTRACT

Transmission lines are vital components of electrical power systems, responsible for the reliable transfer of electricity over long distances. However, faults in transmission lines can lead to disruptions in power supply, economic losses, and even pose safety hazards. Timely detection and accurate classification of faults are essential for ensuring the uninterrupted operation of the power grid. This paper explores the application of the S-transform in transmission line fault detection, emphasizing its effectiveness in extracting fault-related features from current signals. The S-transform is a powerful signal processing technique that combines the Fourier and wavelet transform advantages, offering both frequency and time localization capabilities. In the context of transmission line fault detection, where accurate identification of fault signatures amidst noise and transient disturbances is crucial, the S-transform presents a promising approach. The extracted features of Parseval's energy are fed to machine learning. A 100 % classification accuracy was obtained using the fusion of S-transform and machine learning techniques.

Keywords: MATLAB, ST (S- Transform), Parseval's, SVM, KNN, DT.

I. INTRODUCTION

Transmission lines are the backbone of electricity transmission networks, facilitating the long-distance transport of electricity from generating stations to substations. This enables the integration of diverse energy sources, including fossil fuels, nuclear, hydroelectric, wind, and solar, into the power grid, ensuring a reliable and stable electricity supply to consumers. Robust transmission infrastructure is essential for fostering economic development and industrial growth. Access to reliable and affordable electricity is a cornerstone of modern economies, supporting various sectors such as manufacturing, transportation, healthcare, and information technology. Transmission lines enable the electrification of rural areas, expanding access to energy services and improving the quality of life for communities. Due to the huge importance of transmission lines in the power system, it is essential to protect transmission lines from various faults. So the researchers are always trying to provide the most accurate power transmission line fault detection and classification method. This paper provides an algorithm that combines S-Transform and machine learning techniques for the rapid detection and classification of transmission line faults.

The research work carried out by S.R. Samantaray et al [1] introduced a radial basis function neural network (RBFNN) that has been proposed for fault classification and location estimation after preprocessing the current signals using Hyperbolic. ST. R. K. et al Dubey [2] describe a method that is extensively tested for various fault conditions during a power swing with potential alterations in operational parameters; however, the provided method does not allow for the estimation of the fault site. Y Sheng et al [3] offer a decision tree (DT) based technique for detecting high impedance faults (HIFs). N. Perera et al [4] describe the PNN-based approach that outperforms the DT classifier and Hidden Markov Model (HMM) in accurately identifying fault transients. Maryam Mirzaei et al [5] present PNN as a quick and accurate defect classification, where it is contrasted with radial basis function networks and feed-forward neural networks. Wanjing Xiu et al [6] present a straightforward and precise fault location technique that works for all kinds of faults and doesn't require line parameters. A.A. Yusuff et al [7] present a fault classifier and locator developed using a combination of the Stationary Wavelet Transform (SWT) and SVM, and Aritra Dasgupta et al [8] show an expert system based on wavelet entropy and an artificial neural network for fault classification and distance estimate in an overhead transmission line. The training data set is merely generated for different fault locations, without taking into account variations in fault resistance and fault inception angle. Vaibhav Ghodeswar et al [24] present the application of the wavelet and ANN combination for transmission line fault classification. This paper employs the S-transform for feature extraction and the Matlab Learner application for transmission line fault discrimination. This approach looks at 22 various algorithms, including K-nearest neighbour (KNN) classifiers, decision trees (DT), ensemble classifiers, support vector machines (SVMs) and their subcategories.

II. PROPOSED WORK

Two generator models have been developed in Matlab Simulink. Various faults such as LL, LG, LLG and LLL were created at different locations like 300km, 600km, and 900km and the current signals are recorded for the different types of faults. The following Figure 1 shows Bergeron's transmission line model used.

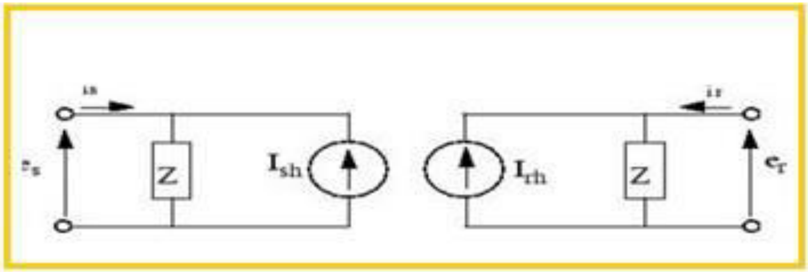

Fig. 1 Bergeron`s Transmission line model

Figure 2 represents a single-line diagram (SLD) for the MATLAB simulation.

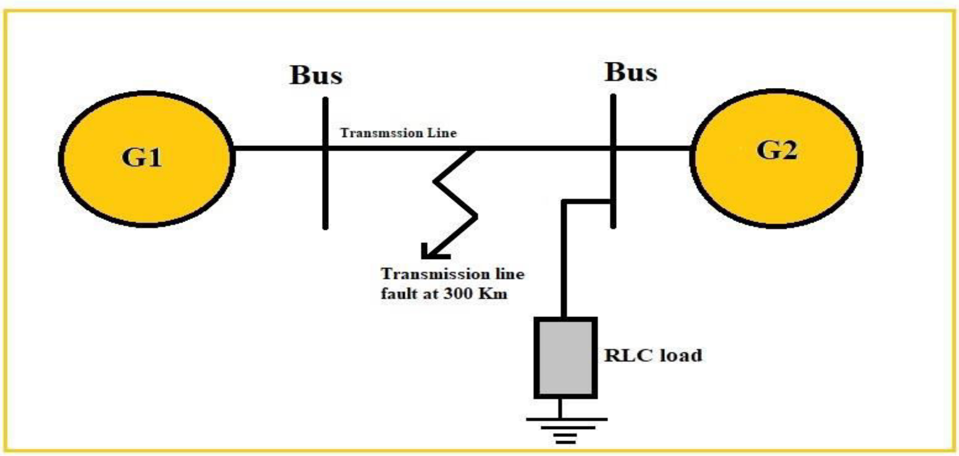

Fig. 2 Single Line diagram (SLD) for the network used.

Table 1 represents components used in the simulation model along with their specifications

Table I: Parameters used for a simulation model of transmission line

Parameter	Specifications
source	
(Vrms)	25e3
F (Hz):	50Hz
R (Ohms)	0.8929
L (H):	16.58e-3
distributed line (Transmission line model)	
Several phases [N]:	3

Line length	300km, 600km, 900km
R per unit	[0.01274 0.3865]
L per unit	[0.9339e-3 4.1267e-4]
C per unit	[12.84e-9 7.751e-6]

Transmission line faults at 300 Km, 600Km and 900Km locations have been created and the fault switching instant is 0.05 to 0.1 seconds. Figure 3 shows the current signature for the LL Fault at the 300 km distance. A sampling frequency of 1 Khz is used for the signal processing process.

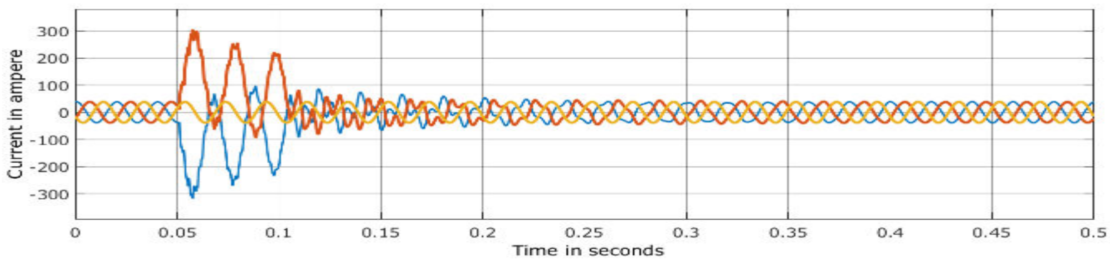

Fig 3: Current Signature of 300 KM LL fault

Figure 4 shows the current waveform of the LG fault at 300KM , Figure 5 shows the current waveform of the LLG fault at 300KM distance and Figure 6 Figure the current waveform of the LLL fault at 300KM distance

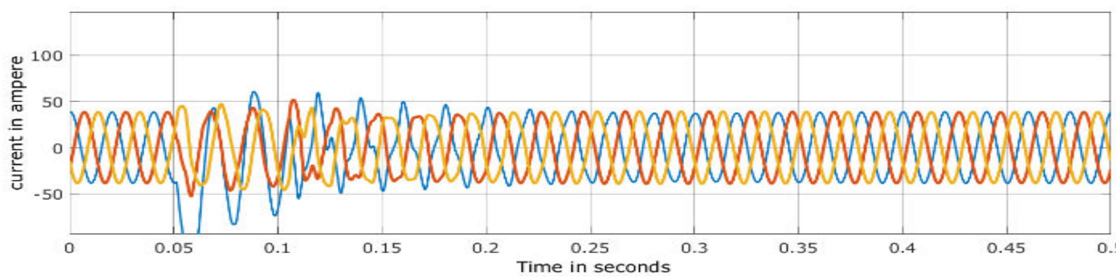

Fig.4: Current Signature of 300 KM LG Fault

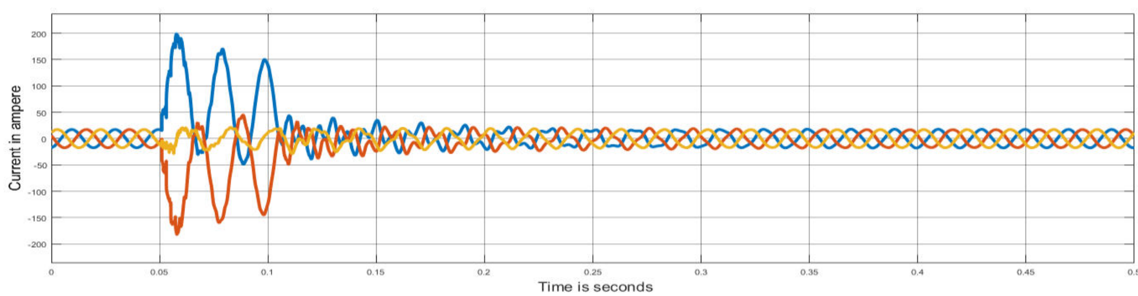

Fig.5: Current Signature of 300 KM symmetrical LLG Fault

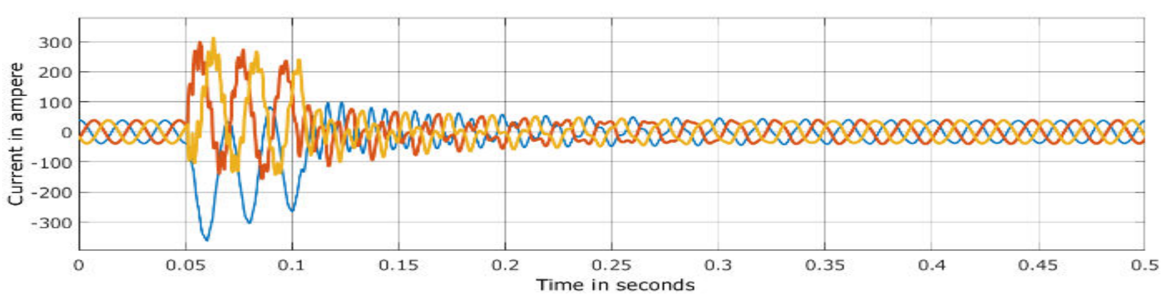

Fig.6: Current Signature of 300 KM symmetrical LLL Fault

Likewise, various current signatures for faults LL, LG ,LLG and LLL at 600KM and 900KM locations are recorded.

III. S-TRANSFORM-BASED FEATURE EXTRACTION

To process transmission line fault signals in the time-frequency domain, this study concentrated on the S-transform.

A. S-transform

The S-transform simultaneously localises the real and imaginary spectra while providing frequency-dependent resolution. Equation [1, 2, 3 and 4] defines the S-transform.

$$S\ (\tau, f) = \int_{-\infty}^{\infty} h(t) g(\tau - t, f) e^{-j2\pi f t}\, dt - - - - - (1)$$

Where h(t) is the signal

(τ) is the Sampling interval

t represents the time and f represents the frequency

g(t) is a modulated Gaussian function

Which is expressed by

$$g\ (\tau) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-(t^2/2\sigma^2)} - - - - - (2)$$

where σ is defined as

$$\sigma = \frac{1}{|f|} \quad - - - - - - (3)$$

σ =function of frequency

The final equation becomes [25]

$$S\ (\tau, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}}\, e^{-(\tau - t)^2 f^{2/2}} \quad e^{-j2\pi f t}\, dt - - - - - (4)$$

The associated time-frequency curve is displayed in Figs. 7, 8, 9 and 10. These contour observations illustrate the frequency and amplitude fluctuations in the period. Thus, the energy calculated at this stage can be an input for the classification of transmission line problems.

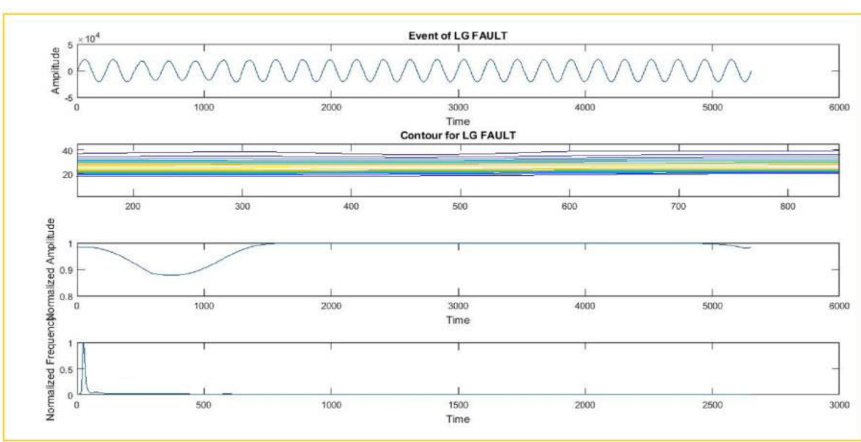

Fig.7: Contour representation for 300KM LL Fault

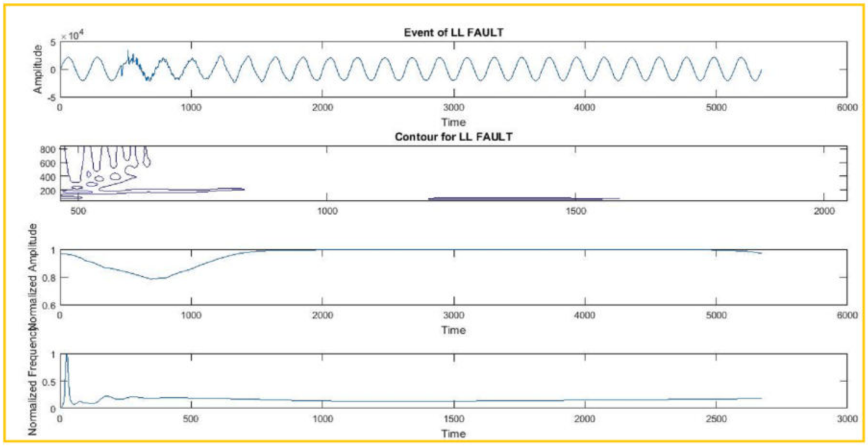

Fig.8: Contour representation for 300KM LG Fault

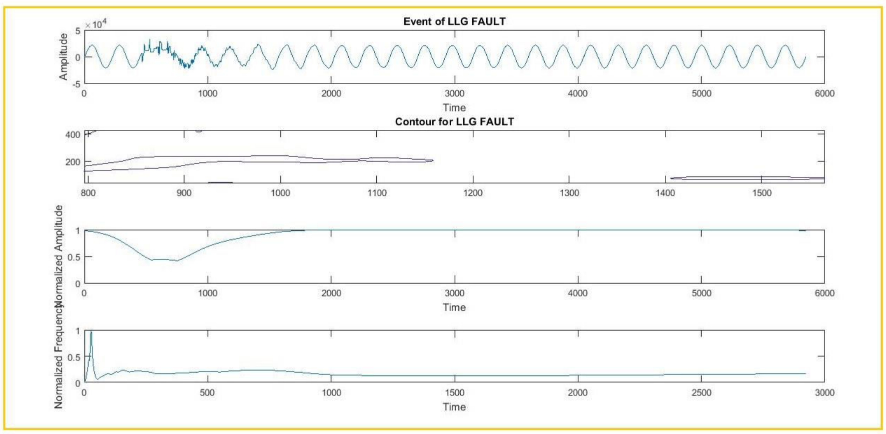

Fig.9: Contour representation for 300KM LLG Fault

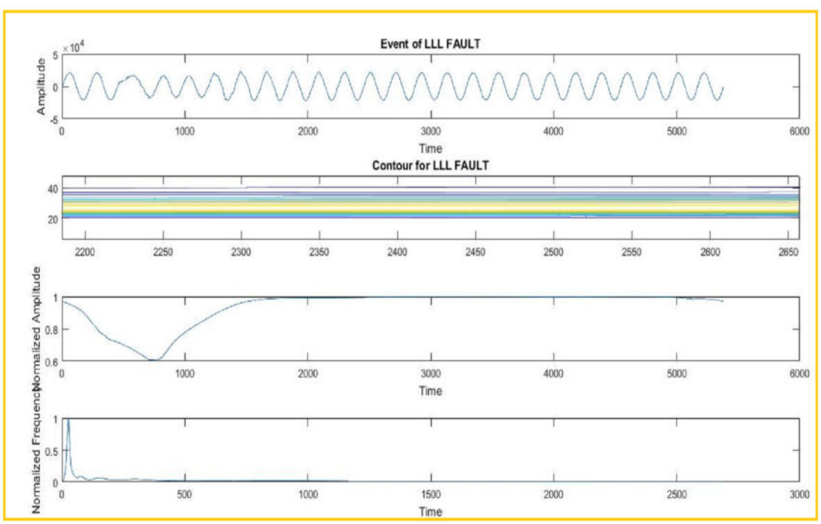

Fig. 10: Contour representation for 300KM LL Fault

Figures 11, 12, 13,and 14 show the 3D views of the Amplitude, Frequency, and Time relations for the different fault`s scenarios.

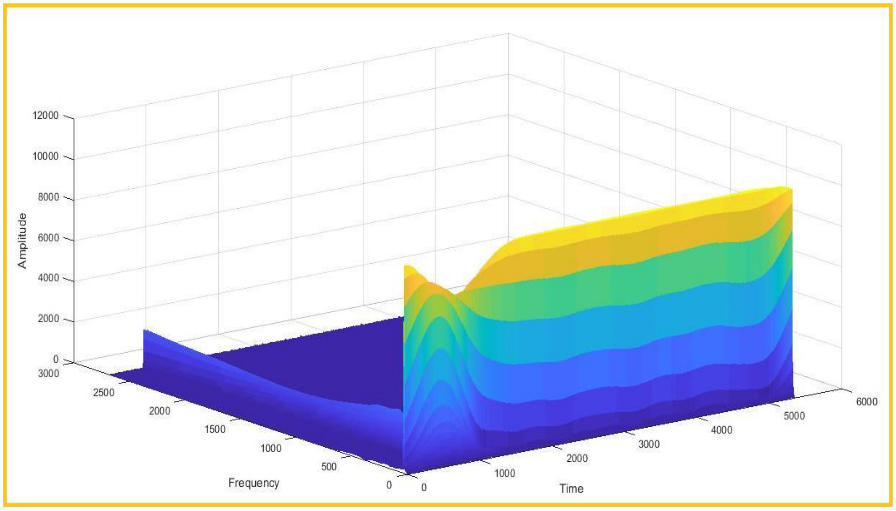

Fig. 11 3D plot for 300KM LL Fault

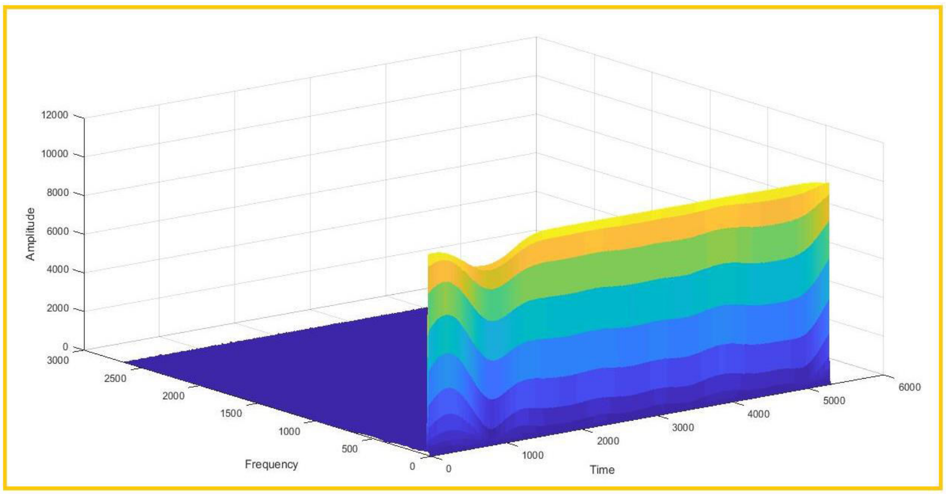

Fig. 12 3D plot for 300KM LG Fault

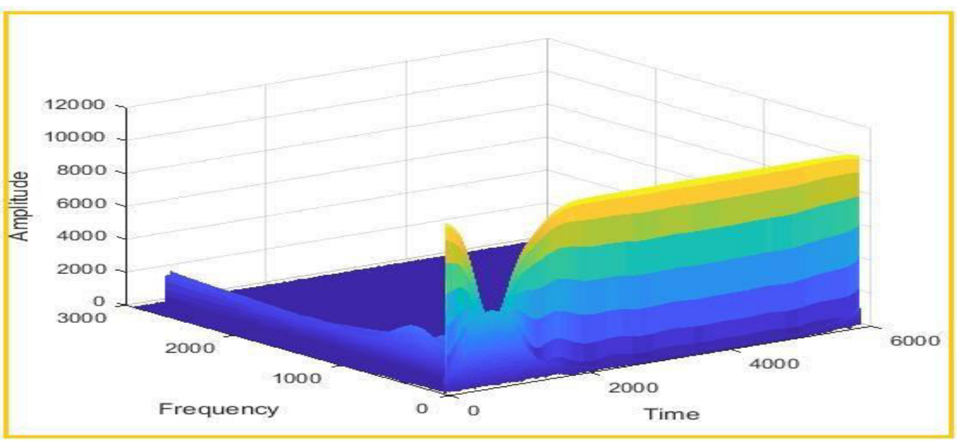

Fig. 13 3D plot for 300KM LLG Fault

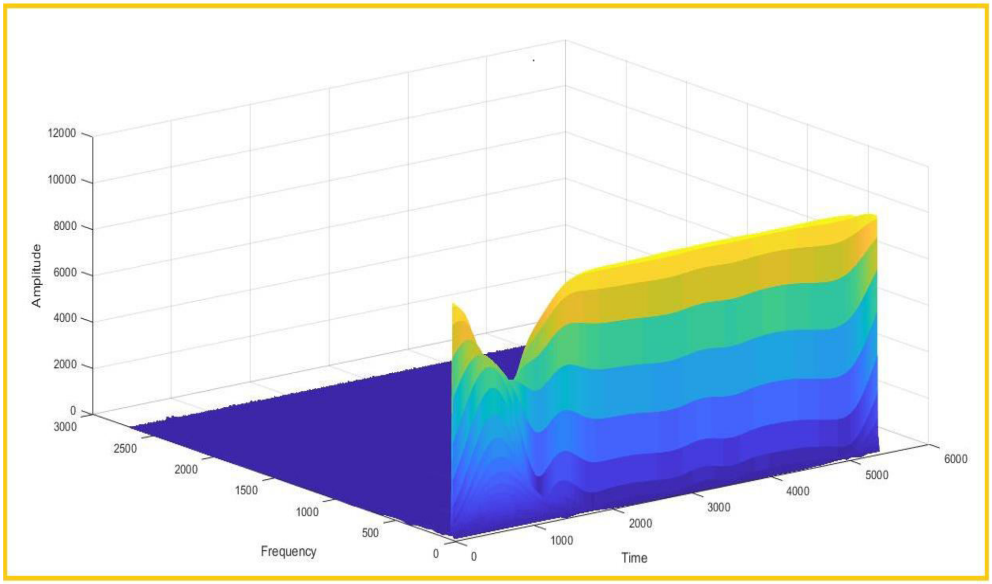

Fig. 14 3D plot for 300KM LLL Fault.

IV.ENERGY LEVELS FOR DIFFERENT FAULTS

Parseval's theorem is useful in signal processing because it enables us to calculate and evaluate the energy of continuous signals via their Fourier transforms [25]. S Transform uses current and the voltage signals as input to extract the contours of various faults. The following equation 5 is used to calculate the energy from camputured current signal.

$$E=\frac{1}{T}\int_0^T (t)^2 dt = \sum_{n=0}^{N} | V\,[N]^2 | \quad \text{---- (5)}$$

In this method, only energy is extracted as a feature for the purpose of power transmission line fault classification.The calculated energy of current signals is presented in the following table.2

Table 2: Energy values calculated for various faults such as LL, LG, LLG and LLL at different locations (300 km, 600 km, and 900 km.)

Fault	**Energy Samples**								
	300 KM			**600KM**			**900KM**		
LL	19.96895	19.52267	10.99802	13.65798	30.89321	30.8621	91.06198	11.25217	91.14425
	26.01819	27.477	11.52327	12.42785	75.87087	82.34574	36.08655	11.48016	33.8067
	29.97216	31.95495	10.40615	10.98126	73.94976	80.3861	41.1927	11.12013	37.99804
LG	18.28795	12.19211	10.99615	21.19062	30.3812	22.25541	19.62324	19.47912	26.03786
	13.94874	15.44303	14.64629	1.28E+02	80.07603	1.13E+02	1.27E+02	1.41E+02	73.60312
	19.57777	23.14599	18.84064	29.73455	69.71188	76.14285	6.57E+01	4.91E+01	5.27E+01
LLG	16.405127	30.32382	27.784989	16.405127	30.32382	27.784989	16.405127	30.32382	27.784989
	13.135015	60.272898	61.664333	13.135015	60.272898	61.664333	13.135015	60.272898	61.664333
	15.600682	60.427099	63.400633	15.600682	60.427099	63.400633	15.600682	60.427099	63.400633
LLL	14.74992	27.33527	28.68186	14.74992	27.33527	28.68186	14.74992	27.33527	28.68186
	22.53765	67.17354	73.7722	12.96985	59.48306	63.54803	12.96985	59.48306	63.54803
	22.53765	67.17354	73.7722	22.53765	67.17354	73.7722	22.53765	67.17354	73.7722

V. CLASSIFICATION TECHNIQUE USED

There are multiple ways for classification of transmission line defects, such as fuzzy logic, Genetic algorithm and ANN but each has its own set of drawbacks. If we consider fuzzy logic for transmission line fault classification, it has the issue of setting the function and fuzzy rules, ANN [24] has a complex training process and the genetic algorithm is computationally expensive, particularly for large datasets or complex classification problems. The time required to converge on an ideal solution rises with the size of the search space. To solve all the above-mentioned issues, a novel approach to classification has been adopted i.e. the classification learner tool, which uses supervised machine learning [23] to train models and to classify the different types of faults.

This method selects features, sets validation methods, trains models, and assesses results. It includes decision trees, discriminant analysis, support vector machines, logistic regression, closest neighbours, and ensemble classification algorithms, it may conduct automated training to find the optimal classification model type.

The real operation of the transmission line fault classification utilizing the combination of MATLAB Learner application and S-Transform is explained by the following flow chart shown in Fig. 15.

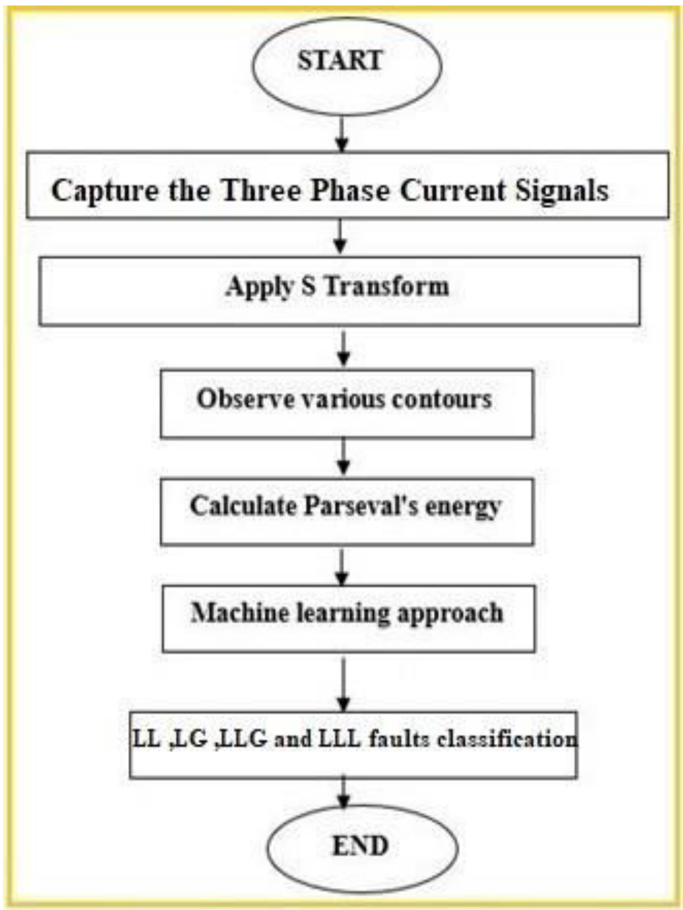

Fig. 15 Flow chart for fault classification

VI. RESULTS AND DISCUSSION

The study used S-transform and Machine Learning to categorize power transmission line faults, detecting energy signals such as LL, LG, and LLL at various distances (300 km, 600 km, and 900 km). Figure 16 depicts the results of machine learning for percentage categorization using MATLAB's learner tool.

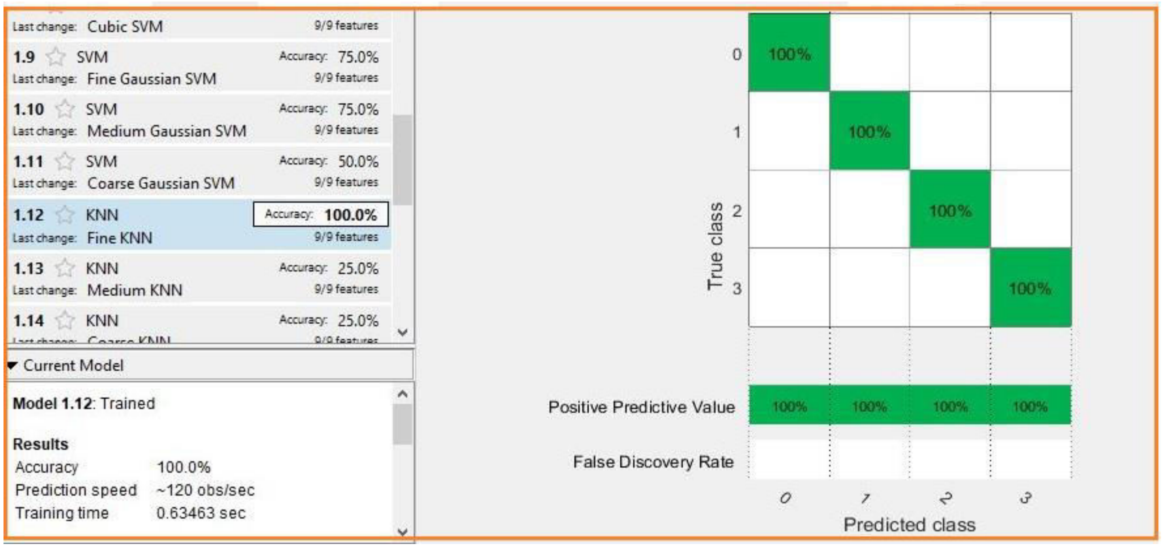

Fig 16 Percentage classification and Confusion matrix output

A 100% classification accuracy was achieved with 40% training and 60% testing (including 7 folds) after a variety of fold, training, and testing combinations were investigated to get the most transmission line fault classification efficiency. Furthermore, the fine KNN output was contrasted with the outcomes of the other 21 classification methods. 100% of power transmission line defects are classified by KNN fine into the LL, LG, LLG and LLL categories.

VII.CONCLUSION

This study proposes machine learning to detect power transmission line faults using the S-transform. The MATLAB Classification Learner tool generates a total of 22 outputs very quickly. The Fine KNN classifier with 40% training and 7 folds achieves the highest classification accuracy of 100%. This research work is very helpful for design of the fast response relay which improves the tranmission line efficiency.

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