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Wavelet Transform (WT) And Support Vector Machine For Fault Detection And Classification On 330 KV Grid Transmission Network

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***Abstract*— In this paper, Wavelet Transform (WT) and Support Vector Machine (SVM) for fault detection and classification on 330 KV grid transmission network is presented. The case study transmission line is a 330 kV 50 Hz, is a 3-phase 71-kilometer transmission line having line resistance of the 0.15 ohms per kilometre and the inductance of 1.326 mill-Henry per phase per kilometre. The Wavelet Transform (WT) was used to extract fault features from the transmission line signal and the results showed that the WT method was effective in detecting the different transmission line faults. The SVM was used to classify the faults. The SVM has accuracy of 0.734712, recall of 0.7636, F1-score of 0.7728 and precision of 0.782. Again, the result of the SVM modelling in python indicated the ability to classify different types of faults in the transmission line, thus providing a pathway to the optimal operation of the protection system on the power network.**

***Keywords*— Wavelet Transform, Support Vector Machine, Fault Detection, Fault Classification, Transmission Network**

1. INTRODUCTION

The advent of Artificial intelligence (AI) and machine learning techniques have resulted significantly in the optimal operation of the power system grid thus reducing the incessant disruptions of the grid network and improving the reliability of the system, this research seeks to address the following challenges currently facing the 330 KV electricity grid network [1,2,3]. The inability of the protection system to promptly identify, classify and isolate the faulty section of the network thus resulting in the colossal damage to power system equipment is one of the challenges, also much effort has been directed towards mitigating the current blackout situation which occurs in some developing countries, caused by failure of the grid network [4,5,6].

The miscoordination of the grid protection system results in the cascading of faults to healthy section of the network, causing frequent and prolonged outages and the increased number of hazards in the electricity grid network could not be unconnected with unresolved and un-isolated fault condition that could not be identified, the research seeks to address human error in relay settings for proper coordination [7,8,9,10,11]. Organizations in the electricity supply industry are facing extreme labour cost and increased burden on the operators and power engineers due to the constraint of knowledge, tool and technology to combat the frequent and persisting faulty condition in the electricity transmission grid network.

Most of the protection relays currently in used do not have the features that enable them to seamlessly identify, classify and predict the occurrence of different types of faults in the grid network with a timely intervention to isolate the faulty system thus increasing the impact of the fault on the entire power grid and degrading the system's reliability and the availability of electricity supply [12,13]. This is mostly due to relay settings and human error. Accordingly, in this paper, Wavelet Transform (WT) and Support Vector Machine (SVM) for fault detection and classification on 330 KV grid transmission network is presented. The work is mean to provide the fault detection and classification system which will enhance the operation of the case study protection system in the transmission line network

2. METHODOLOGY

2.1 THE DESCRIPTION AND MODELING OF THE CASE STUDY 330 KV GRID TRANSMISSION NETWORK

The case study transmission line is a 330 kV 50 Hz, three phase 71-kilometre Odukpani – Ikot Ekpene transmission line having line resistance of the 0.15 ohms per kilometre and the inductance of 1.326 mill-Henry per phase per kilometre, along with other line parameters as shown in Table 1. The transmission line used for the study was modelled using MATLAB and Etap software as shown in Figure 1 and Figure 2.

Table 1 The Transmission Line Parameter

S/N	Variable	Value	Units
1	Base MVA	500	[MVA]
2	Base Voltage [L-L RMS]	330	[KV]
3	Base Frequency	50	[Hz]
4	Phase Angle	38.87	[deg / Km]
5	Line Resistance per phase	0.1500	[ohm]
6	Line Inductance per phase	1.3263	[mH/ Km]
7	Length of transmission line	71	[Km]

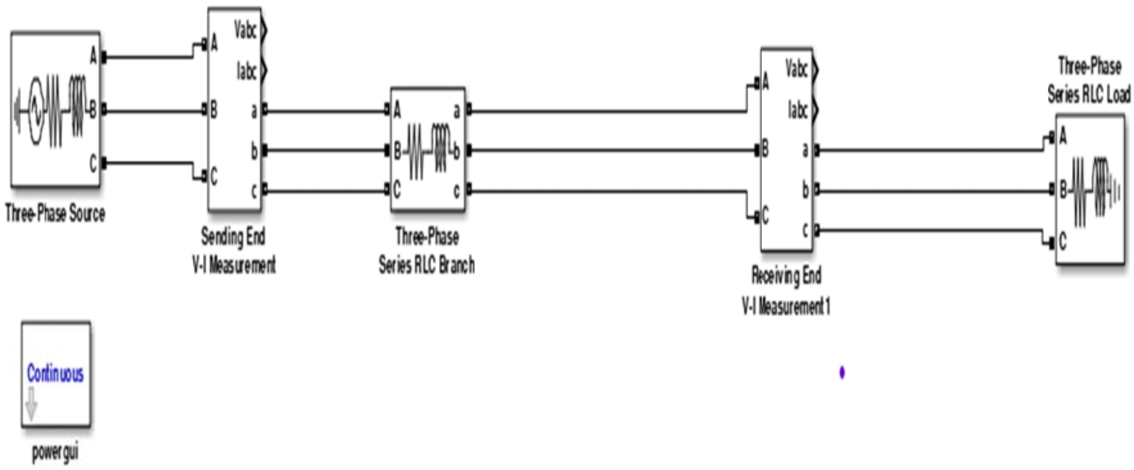

Figure 1: Simple two-bus transmission line system

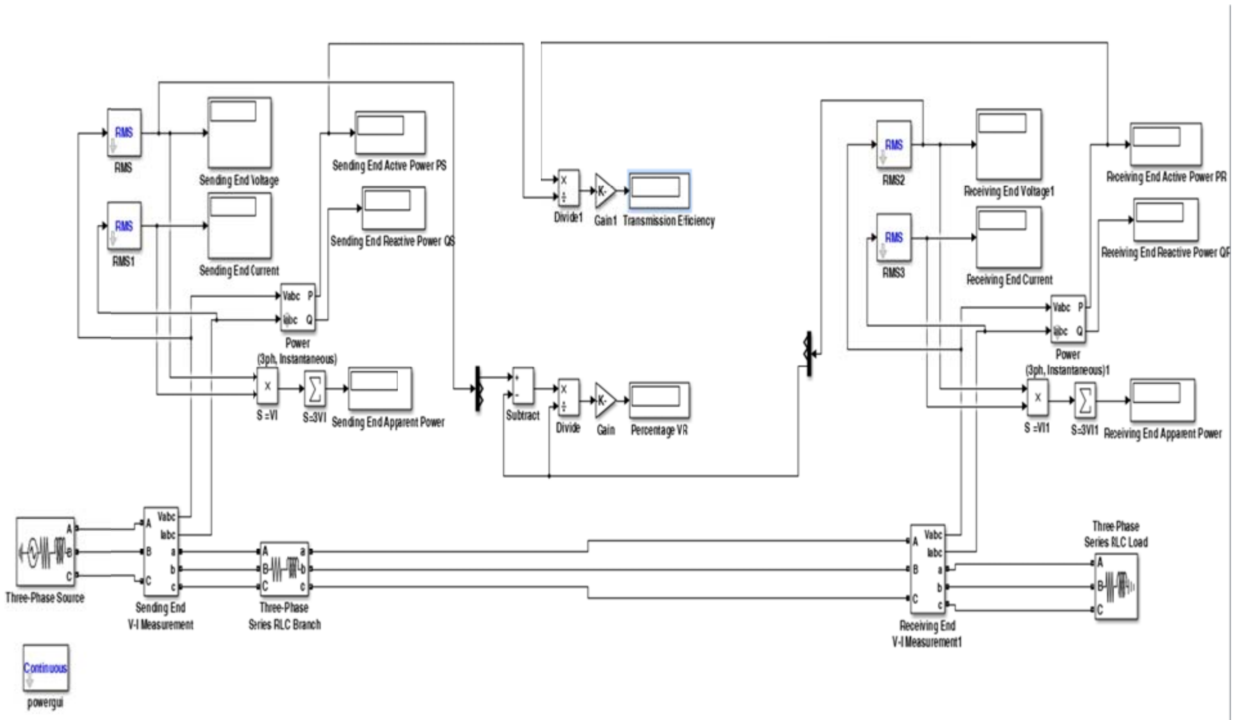

Figure 2. The MATLAB Simulink model of the case study transmission line

2.2 Wavelet Transform (WT) and Support Vector Machine model for Fault Detection and Classification

Wavelet Transform (WT) is a signal processing tool which extracts information from the transmission line using the voltage and current measurement. It is mostly used in unveiling hidden information from the signal using the fault current and fault voltage from the grid network. The case study transmission line was modelled in MATLAB Simulink as shown in Figure 1 and Figure 2. The Wavelet transform is in form of oscillatory waveform with a zero average value amplitude that occurs briefly and decays very fast to zero. In Wavelet transform, information is extracted from the signal by decomposing such signal into the different components at different scale and different frequency bands as captured in Figure 3 and Figure 4.

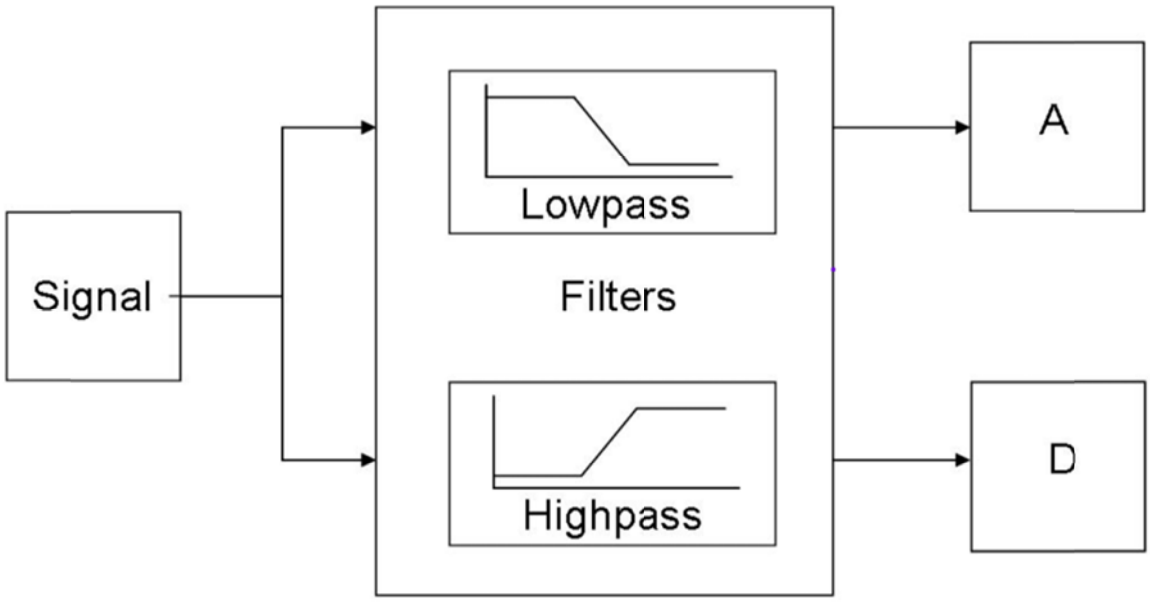

Figure 3. Low pass and High pass filter

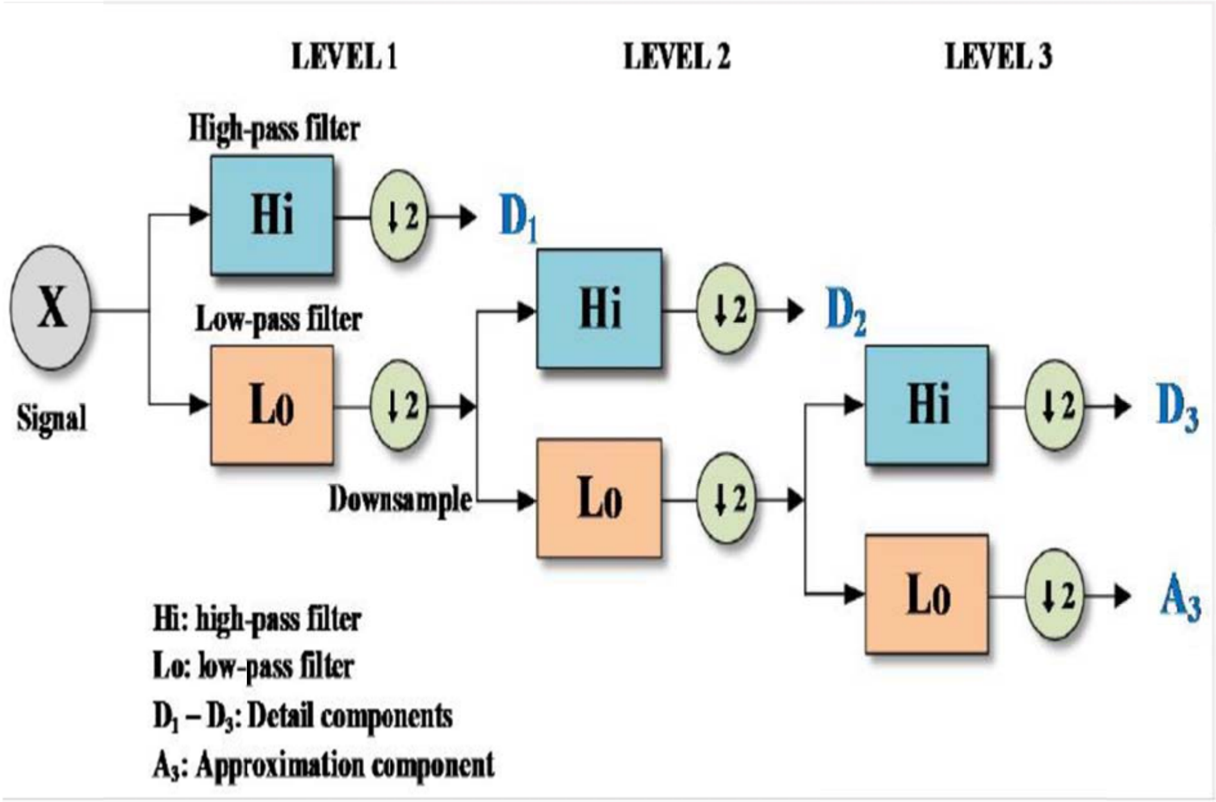

Figure 4. Signal decomposition levels

The Low pass filter in the WT model produces the approximation components of the original signal while the High pass filter provides the detailed components of the decomposed signal. Using the detailed components in the WT model, faults in the power system are identified and classified.

The MATLAB code for the Wavelet transform model included the following syntax.

[c,1] = wavedec(x,n,wname);

Where,

(i) Wavedec denotes the function that decomposes the signal,

(ii) x denotes the signal,

(iii) n denotes the wavelet layer (1 = default)

(iv) c denotes the output wavelet decomposition vector

(v) 1 denotes the number of coefficients by level

The following wave transform syntax was used for detailed coefficients of signal in our study.

D = detcoef(C,L,N)

where,

(i) detcoef denotes the functions which is used to obtain the detailed coefficients of the signal,

(ii) c denotes the output wavelet decomposition vector

(iii) 1 denotes the number of coefficients by level

(iv) n denotes the number used to identify the wavelet layer (1 = default)

Next, a fault block was introduced into the model already created as shown in figure 3.6 and confirmed on MATLAB Simulink. The fault block was used to introduce different types of faults into the 330 kV transmission line. For better outcome, wavelet-based feature extraction, fault detection and classification in the power system requires that a threshold value be set. The threshold values are not generic as different power system profile requires its own sets of threshold values.

To overcome these challenges and limitation, the machine learning technique (Support vector machine) was used with the Wavelet transform to improve the accuracy of feature extraction, fault detection and classification on the 330 kV transmission grid network.

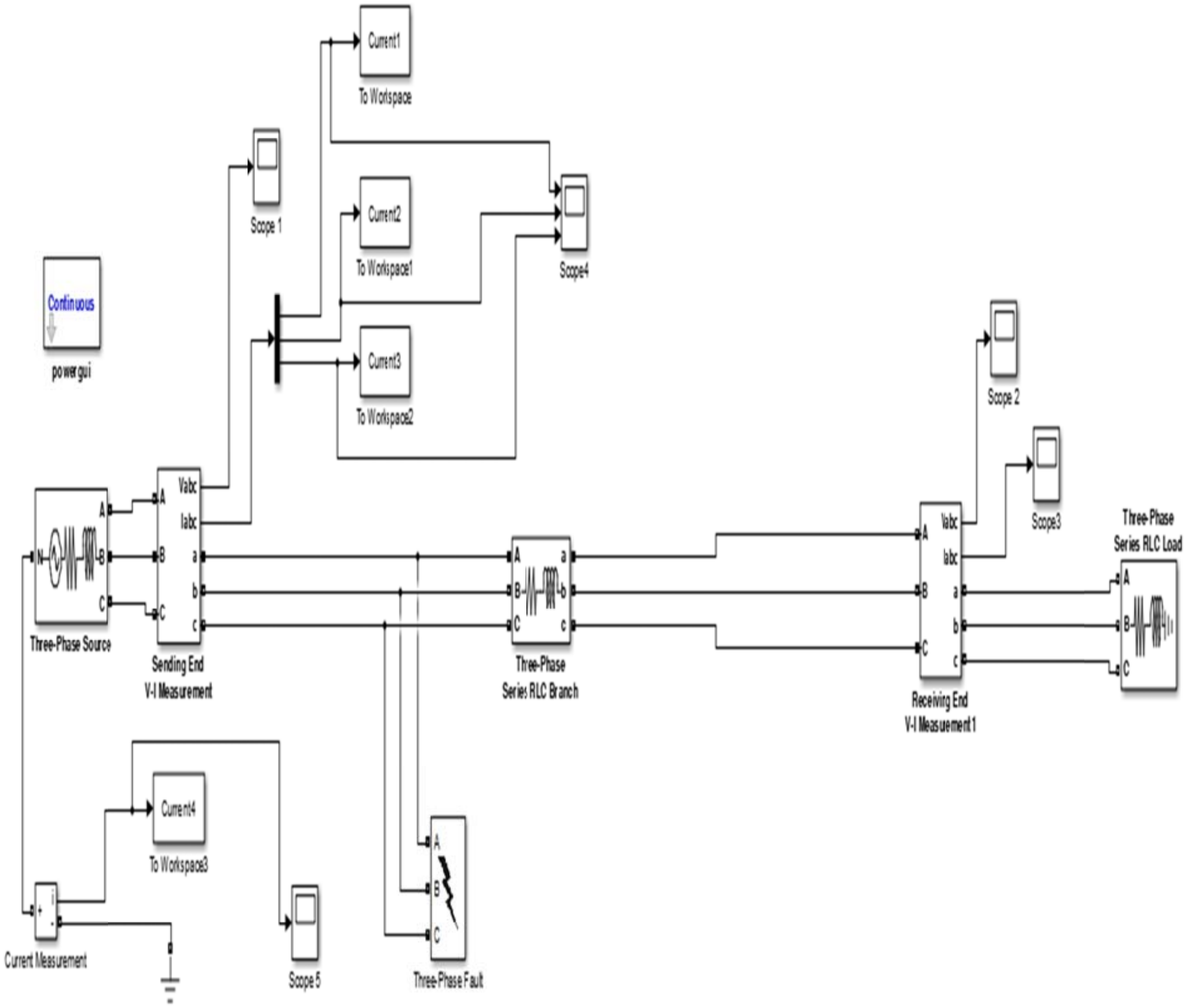

Figure 5. The Wavelet Transform (WT) and Support Vector Machine (SVM) model to detect and classify faults on transmission line

In developing the 330 KV power grid model in MATLAB Simulink, as depicted in Figure 5 , the 3-phase source block and 3-phase measuring block were used along with the 3-phase series RLC branch block which acted as the transmission line, while at the same time the 3-phase series RLC block was used to represent the load. Furthermore, the in the fault identification and classification, the three phase current measurements were used along with the measurement of the neutral current. A De-mux (Demultiplexer) block was used to separate the currents. In order to use the current measurement in the Wavelet transform (WT) the "To workspace" block called SimOut was used. Three of these blocks were used to represent current 1, Current 2, and Current 3. The SimOut (To workspace) was connected to a scope to measure the 3-phase currents of Phase A, Phase B, and Phase C.

Also, for the purpose of measuring the neutral current to distinguish between line-to-line faults and double lines to ground faults, the 3- phase source block was changed in the configuration section to Yn in order to have the neutral point, and then an Ammeter block and a ground block were connected to the neutral point. Also, the "To workspace" block was added to provide the Current 4 measurement while a Scope was connected as optional.

To apply fault in the model, a 3-phase fault block was added to the model and connected appropriately as shown, the switching time on the block was chosen by double clicking on it and the parameter was changed and a time of 0.05 seconds was chosen. To use the WT to detect any type of fault, a MATLAB code was written as a script, in the code "db4" Daubechies-4 wavelet type was used.

When WT is applied on a signal and its numbers of coefficients are obtained, it was expedient to have another command that was used to extract detailed coefficients to know further information, a syntax 'detcoef' was used as the function that obtained the detailed coefficient of the signal. The maximum value of the coefficient in each phase was used to distinguish between different types of faults. It was seen that when fault occurred in any phase, the coefficient in that phase had very high magnitude while the coefficient in the other phase has zero or very low magnitude, which means that at no fault situation in the power system, the coefficient in all phases becomes zero or very low, and this made it possible to distinguish between the different types of faults.

3. RESULTS AND DISCUSSION

The outcome of the initial WT model using Daubechies 4 (db4) in MATLAB was recorded as in Table 1. The dataset was then divided into testing and training datasets by the python software, covering twelve different types of fault on the 330 KV grid transmission line. When there was no fault, the output that was expected from the identifier and classifier was zero (0), however, in the presence of fault, the expected output of the model for the different phases was one (1) as shown in the Table 2.

It was further observed that as soon as fault occurred, the current output for the different phases increased astronomically as shown in Figure 6 to Figure 16, confirming the effectiveness of the fault identification and classification technique using machine learning techniques.

The voltages and currents were seen to behave in different ways during the occurrence of the different types of faults. Immediately there was a fault in the system, the voltage of the phase was seen to decrease while the current of that phase was seen to increase throughout the interval of the faults, and these were seen to vary differently from the healthy phase. This is one of the reasons circuit breakers are designed to accommodate both the normal, abnormal, running current and the heavy closing and opening current of the system in kilo-Ampere (kA) especially during the operation of the protection relays. As the faults occurs this selected feature of the harmonics showed abnormalities at 0.8 to 1 millisecond as shown in Figure 6 to Figure 16. The SVM training performance as a fault classifier is presented in Figure 17.

Table 1 The Transmission Line Parameter

Measurement	[Unit]	Sending End	Receiving End
Voltage	[KV]	2.103e+05	1.872e+05
Current	[A]	858.9	858.9
Frequency	[Hz]	50	50
Phase angle	[deg]	4.12	36.87
Active power	[MW]	4.09e+08	3.854e+08
Apparent power (P)	[MVA]	5.404e+08	4.81e+08
Reactive power (Q)	[M var]	3.543e+08	2.889e+08

Table 2: Result of the simulation for fault detection

Types of Faults	Max. Coefficient of Phase A Current (m)	Max. Coefficient of Phase B Current (n)	Max. Coefficient of Phase C Current (p)	Max. Coefficient of Ground Current (q)
3Phase to Ground (ABC-G)	36.5997	305.7004	158.0157	2.8877e-07
AB – G	36.8995	305.2295	0.8561	156.5601
AC – G	36.664	6.5366	158.0823	299.3732
BC – G	3.3052	306.2759	157.6493	34.0273
A – B	115.1798	182.2653	0.8558	0.0287
A - C	92.0952	6.5370	66.6691	0.0015
B – C	3.3058	279.5540	174.6624	5.2860e-04
A – G	36.9665	6.5366	0.8561	52.8706
B – G	3.3052	305.8062	0.8561	190.5215
C – G	3.3052	6.5366	157.7163	264.3991
NO FAULT	3.3052	6.5366	0.8561	9.8765e-12

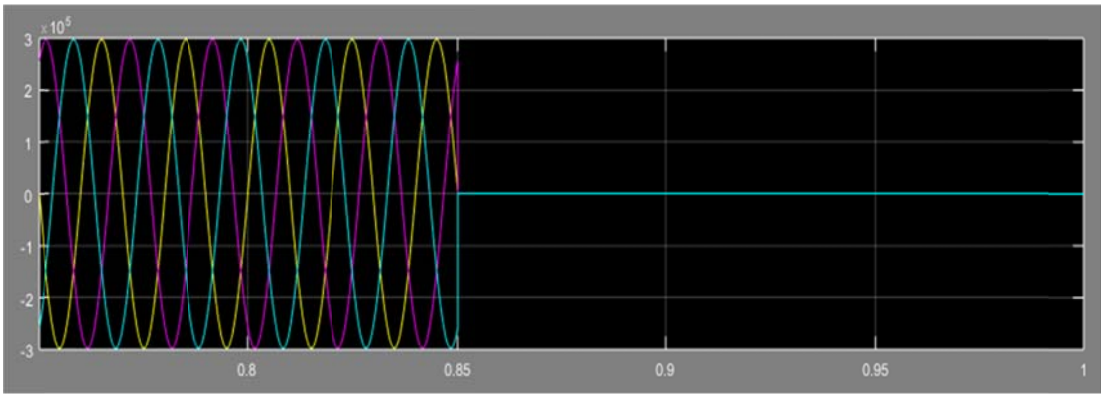

Figure 6 Vabc-g

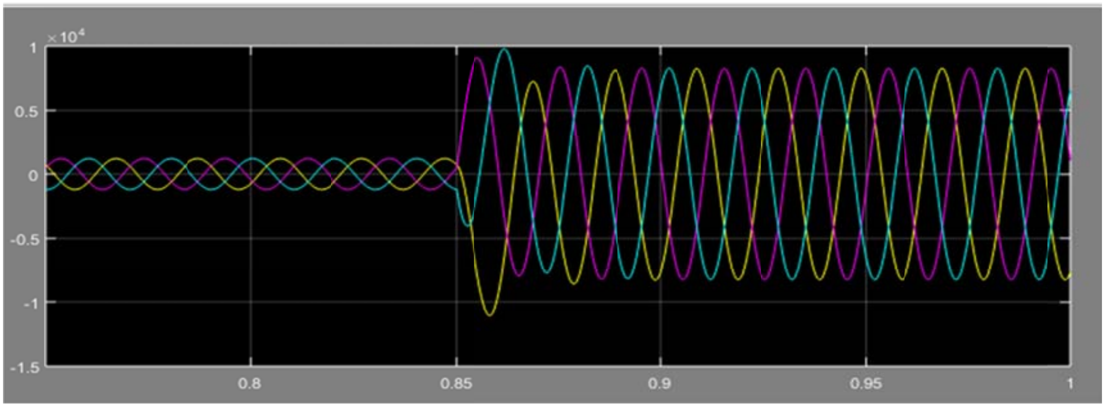

Figure 7 Iabc-g

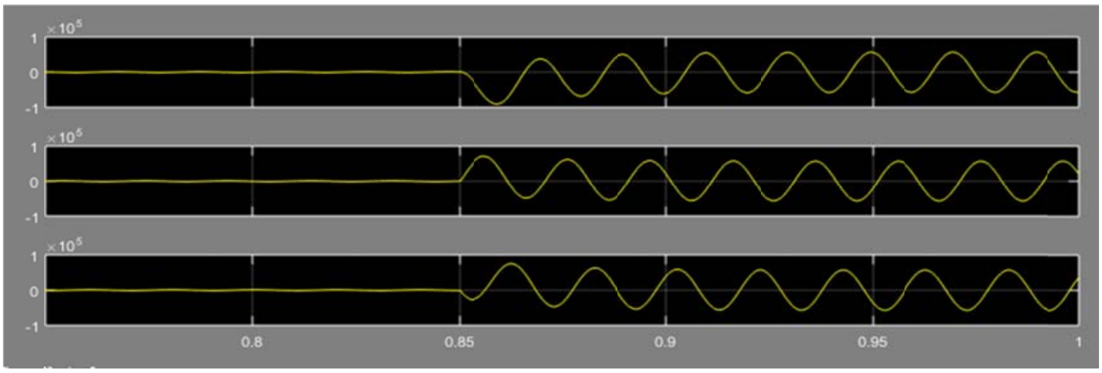

Figure 8 Iabc-g

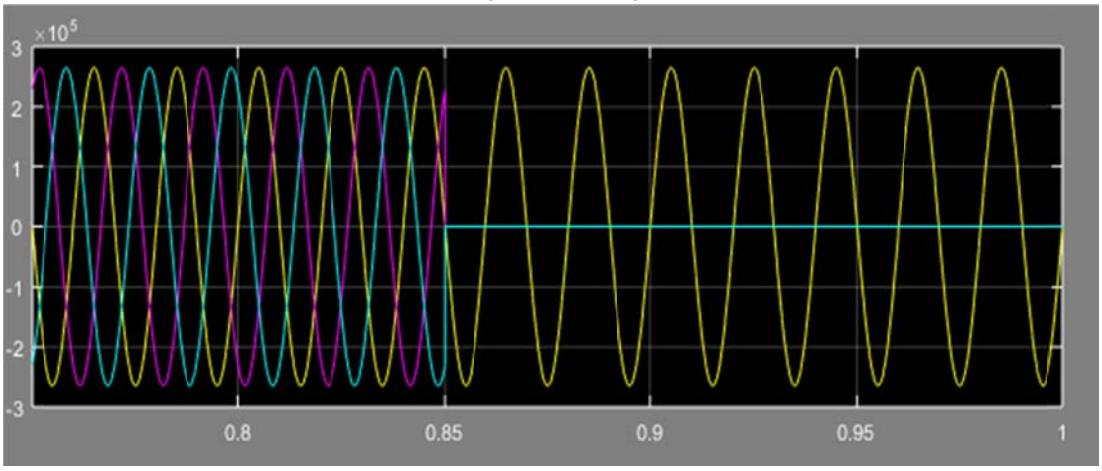

Figure 9 Vbc-g

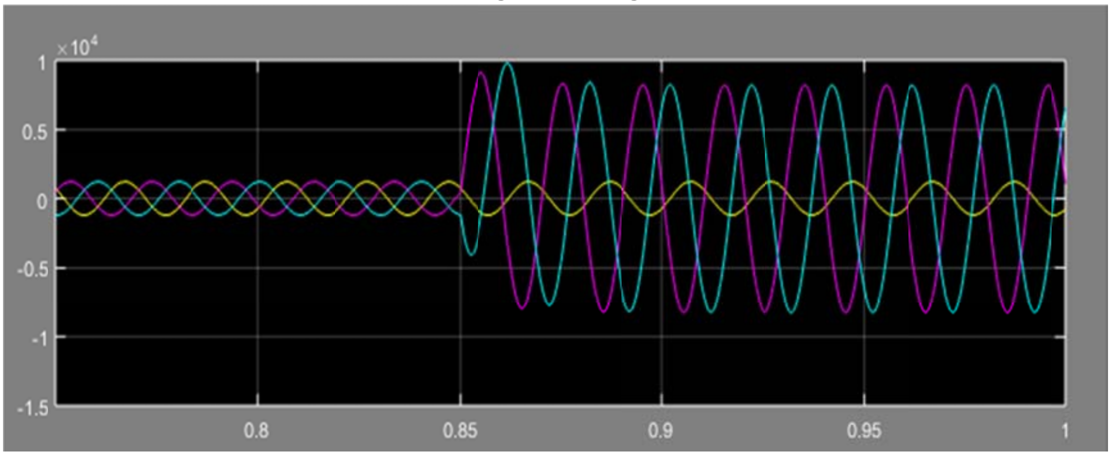

Figure 10 Ibc-g

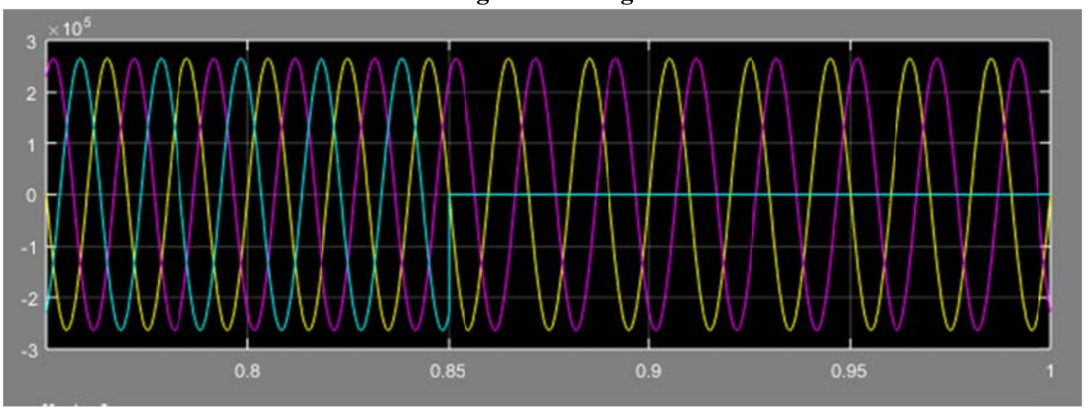

Figure 11 Vc-g

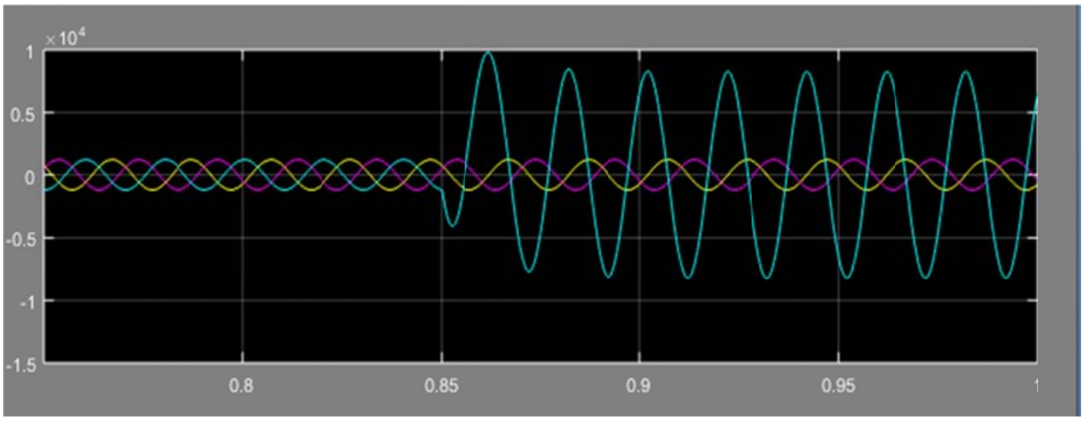

Figure 12 Ic-g

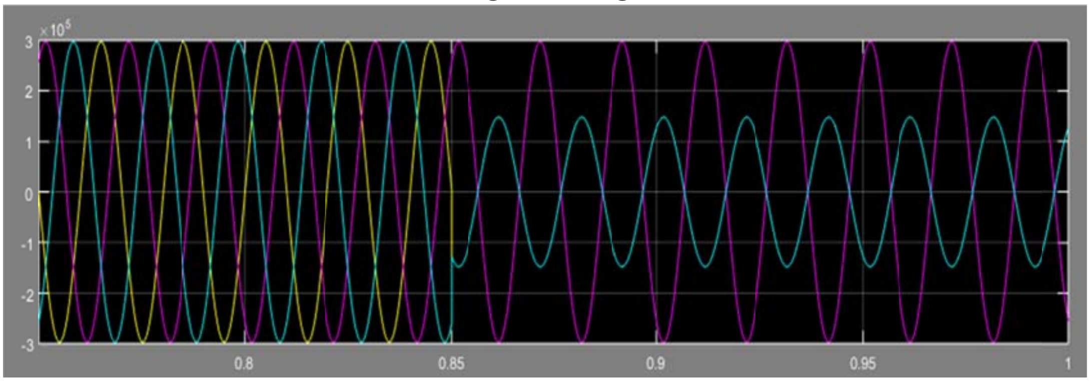

Figure 13 Va-c (two phase faults)

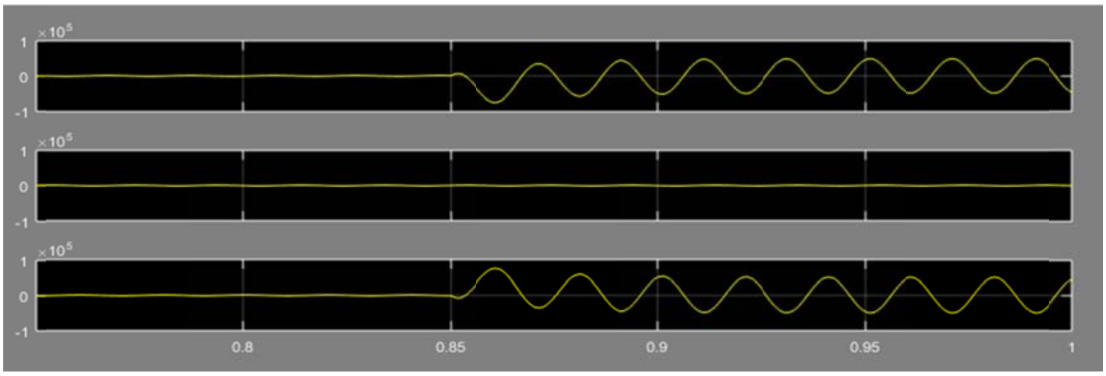

Figure 14 Ia-c (two phase fault)

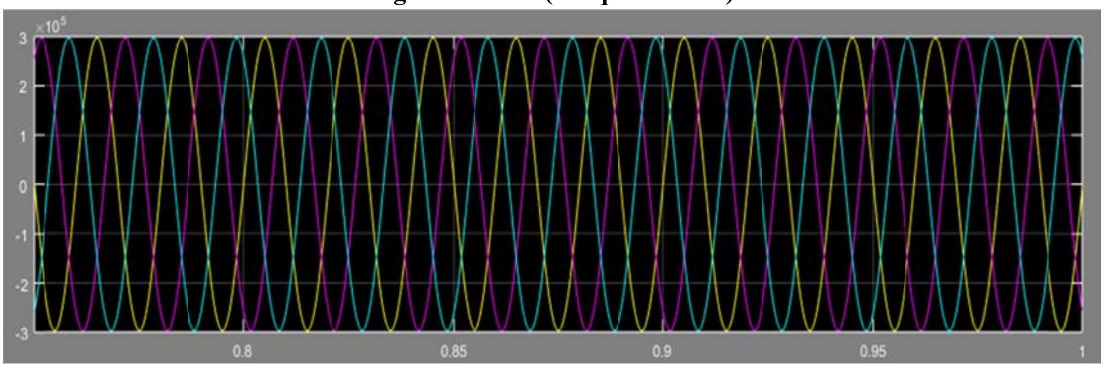

Figure 15 Vabc (3-phase Voltages) at no fault situation

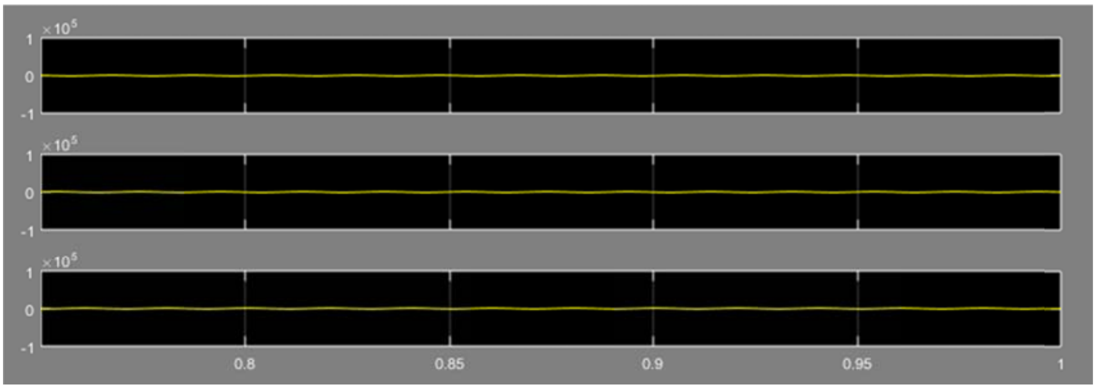

Figure 16 3-phase Currents at no fault situation

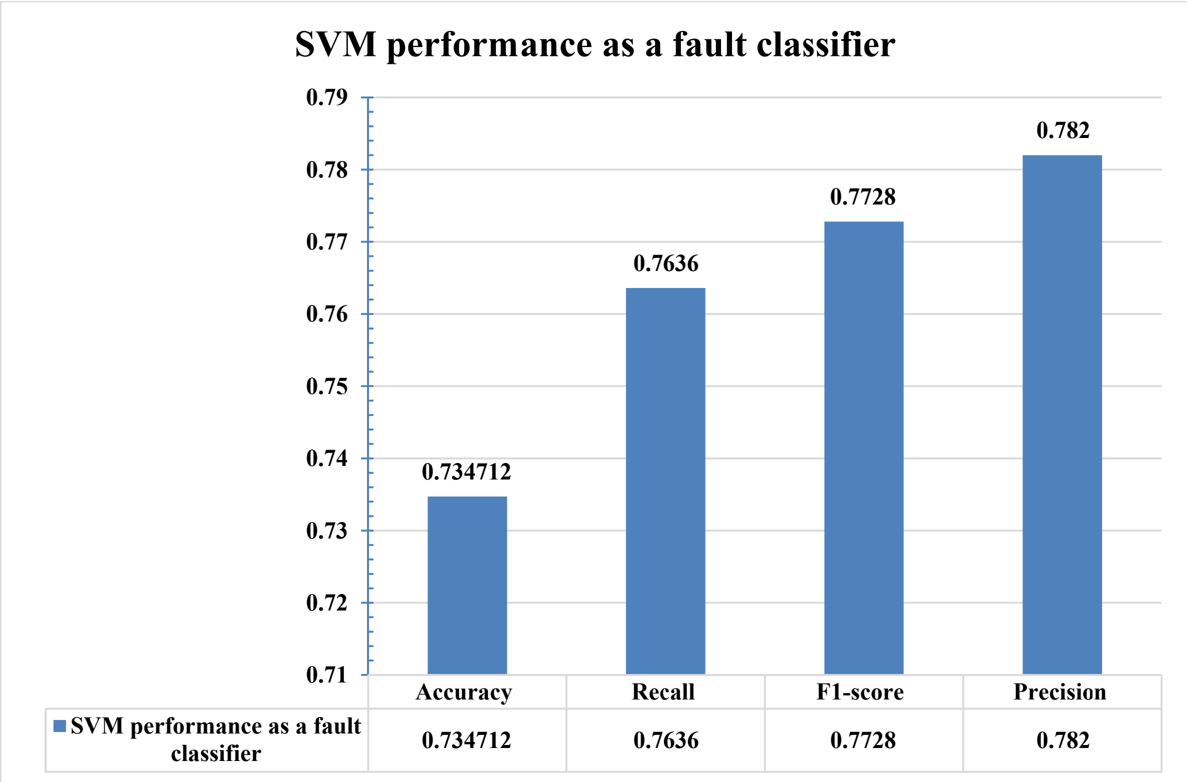

Figure 17 SVM performance as a fault classifier

4. CONCLUSION

The application of wavelet transform and Support vector machine model for feature extraction, detection, prediction, and classification of faults on a 330 KV transmission grid network is presented. The Wavelet Transform (WT) was used to extract fault features from the transmission line signal and the results showed that the WT method was effective in detecting the different transmission line faults. In addition, the result of the SVM modelling in python indicated the ability to classify different types of faults in the transmission line, thus providing a pathway to the optimal operation of the protection system on the power network.

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