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Situational Awareness Enhancement in Transmission Lines using NI Based PMU

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Abstract: Phasor Measurement Units (PMUs) are becoming prominent in enhancing the situational awareness in wide area power system monitoring, thereby playing a vital role in its protection and control. This paper focuses on enhancing the situational awareness of transmission line using National Instruments (NI) based PMU. The data measured by the virtual PMU is used for fault detection and fault classification. The detection and the classification in the LabVIEW platform are performed using the Fourier Transform and support vector machines (SVMs) respectively. The proposed methodology has been applied on a laboratory set up consisting of transmission line, three phase load and an NI based PMU. The enhanced situational awareness in the detection and classification of transmission line faults helps in restoration of the transmission line as quickly as possible and trigger wide area control actions to maintain power system stability against the disturbances created by a fault.

Keywords : Phasor Measurement Unit, Park's Transform, Machine Learning, NI cRIO, Situational Awareness.

I. INTRODUCTION

With the advent of PMUs, the conventional power system is transforming into a smart power system (SPS). PMUs provide real-time voltage phasor and current phasor along with a global positioning system (GPS) time stamp. SPS equipped with PMUs will be more suitable, because of the accurate real-time monitoring and control of grid dynamics. However, the faults on transmission lines, influence the stability and suitability of SPS. Any delay in clearing the faults leads to cascaded failure on the system. It is therefore very much essential to become aware of the situation of the transmission line. In order to study the situational awareness of the transmission line, it is of utmost importance to develop a methodology that recognizes the occurrence of the faults and able to classify the type of fault.

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This kind of information assists in initiating the fault location algorithms to bring back the transmission line into operation. Fig. 1 shows the schematic diagram of the transmission line situational awareness. The first task is to detect the disturbance and then comprehend the type of fault. Finally, the location of fault has to be predicted. Based on the situational awareness analysis of transmission line, a decision is taken and the fault line is isolated to protect the healthy line. Different protection schemes for detection, classification and location of the fault have received a lot of attention from many researchers. In [1] a review of fault detection, classification and localization methodologies without using PMUs has been presented. In [2] an adaptive fault identification and classification methodology for smart power grids employing PMUs using support vector machine (SVM) based on the equivalent voltage and current phase angle has been proposed. However, the findings are based on the simulated and offline data and the authors have not considered the online implementation of the proposed work. Similarly, a support vector machine based fault localization methodology using PMU measurements has been proposed in [3]. A fault location methodology on three terminal lines by using two terminal synchronized voltage and current phasors has been proposed in [4]. The analysis carried out using the supper imposed positive sequence components by identifying the faulty leg first and then fault location. In [5] a fault location method using PMU data by transforming the fault location as a sparse matrix problem based on the ratio of the serial impedance of each side of the fault point for locating the fault has been proposed. A fault detection and classification algorithm were presented in [6] using Stockwell transformation employing the current sample over a half cycle prior to detection of disturbance. The classification was on the basis of the comparison of energy of three phase current and zero sequence current with fault threshold. The simulation was carried out using MATLAB Simulink. In [7], a fault detection and classification method was presented to detect and classify the disturbance in transmission system using space-time analysis for detection and K-mean algorithm for classification using the PMU data. In [8], a wavelet based event detection method was presented using the instantaneous voltage and frequency of Korea Electric Power Corporation Transmission line. The analysis was carried out using offline stored PMU data. In [9], a fault detection, classification and localization technique is presented using wavelet packet decomposition and radial basis function neural network (RBFNN) in High Voltage AC transmission line taking only current signal into consideration. In [10], a principal component analysis based fault detection, classification and localization methodology was presented using a signature which is generated from a quarter cycle of the phase current of a transmission line system. In [11], a Convolutional Neural Network (CNN) based faulted line localization was presented using the bus voltages, which can be able to localize even under as lower as 7% of bus observability.

The result was validated using the simulation of IEEE-39 bus and 68-bus power system. In [12], a fuzzy logic rule based fault classification is presented using the three phase current at the one end of the transmission line. The work was validated using EMTP and MATLAB simulation by considering various fault locations, fault inception angle, load angle and fault resistance. These analyses are very useful in becoming aware of the health of transmission system by analyzing and studying the fault profile and then protecting it from the upcoming disaster. To the best of the author's knowledge, most of the literature reported so far were dealt with the analysis of off-line simulated data employing with the available simulation tools. Some of the researchers performed

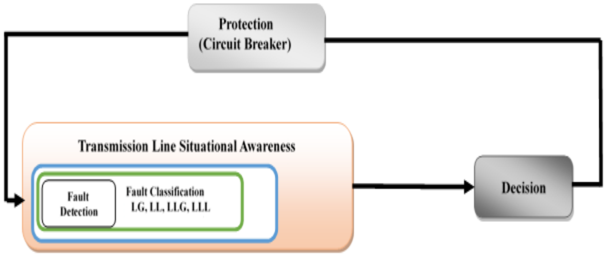

Figure. 1 Transmission Line Situational Awareness

post fault analysis of the PMU data collected from utilities [8], [13]-[16]. The researchers have not focused on how these digital signal processing techniques can be applied online on the real system by capturing the voltage and current data online and analyze the fault online being with the real practical system.

National Instrument (NI) based PMU facilitates the efficient online simulation on the real time voltage and current data with higher and faster sampling rate combining with high speed digital signal processing on the FPGA processor, which will enable the online event analysis. Reference [17] proposed a phaselet technique to detect the fault rapidly resulting into expeditious situational awareness of transmission line.

In this paper, a transmission line fault detection, classification and localization methodologies has been achieved with the help of NI based PMU (cRIO based PMU) with detection of fault within few milliseconds, classifying the fault type, predict the localization of fault and protect the transmission line with greater speed. This paper focuses upon fault analysis of real-time online data obtained using NI based PMU (with reduced voltage and current level). A LabVIEW based SVM technique has been employed for fault classification and localization. The proposed method is able to detect, classify and localize the transmission line faults. In addition, a transmission line protection scheme is used to protect the faulty branch when the fault has occurred and thus enhancing SA of the transmission line. The result is compared with a SEL-311C transmission protection system relay to validate the results for the same system. The main contribution of this work is that, it can be used physically on the practical transmission line and it can protect the system by operating the breaker when an event is detected within a few milliseconds and reclose the breaker after the fault is cleared automatically. A brief discussion on NI based PMU is presented in section 2. Section 3 depicts the proposed methodology. The results and the discussions are presented in section 4 followed by conclusion and future scope in the section 5.

II. NI BASED RECONFIGURABLE PMU

The block diagram for the proposed National Instruments (NI) based reconfigurable PMU is shown in Fig. 2. The main components of the proposed NI based reconfigurable PMU are: NI cRIO 9066, NI 9246, NI 9242, NI 9467 and NI 9401. These components are described in this section.

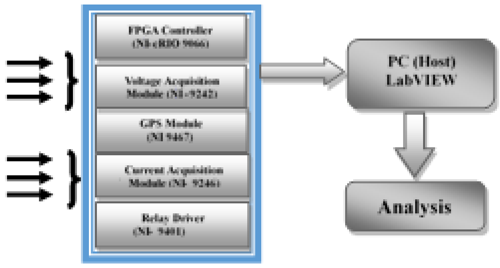

Figure. 2 NI based PMU system

1. NI cRIO 9066 is an embedded real-time controller with reconfigurable field-programmable gate array (FPGA) for C series module. It is useful for the advanced monitoring and control applications. It comprises of 667MHz dual-core CPU with, 256MB DRAM.

2. NI-9246 is a C series current input module of 20Arms, 30A peak to peak, and 24 bit with 3 channels.

3. NI-9242 is a 250V rms L-N, 400Vrms L-L, 50-Kilo samples/second/channel (kS/s/Ch), 24-bit, 3-channel C Series voltage input module. Its ability of wide measurement range makes it possible for the high-voltage measurement applications such as phasor measurements. NI based current module and voltage module represents the current transformer (CT) and potential transformer (PT) of the conventional PMU.
4. NI-9467 is a GPS C series synchronization module. It provides accurate time synchronization for cRIO-9066 along with the location (latitude and longitude). It is used for accurate data time stamping and getting data acquisition based on the arrival of the pulse per second (PPS).
5. NI 9401 is a 5V/TTL, 8 channels, 100ns C series digital module. It is a configurable digital I/O interface for the input or output in 4 bit increments. Based on the information obtained from NI based PMU, NI 9401 will create a triggering signal to the relay associated with the faulty line which in turn helps to isolate only the faulty portion of the system from the rest of the healthy portion of the power system. The features which a NI based PMU is capable of possessing can be perfectly dovetailed to enhance the situational awareness of the transmission line.

III. FORMULATION OF PROPOSED METHODOLOGY

The methodology used for fault detection, classification and localization are described in this section. The block diagram of the proposed system is shown in the Fig. 3 and its experimental setup is shown in Fig. 4. It consists of a three-phase source, three-phase transmission line, and three phase balanced load.

The parameters of the transmission lines and that of the load which were used in this work are mentioned in the Table 1.

The hardware used for acquiring the real-time voltage and current signals from the transmission line is interfaced with a high speed 4.20 GHz Quad-core Dell Precision 3620 workstation installed with LabVIEW 2017 version software. The data from the hardware is sent to the workstation through gigabyte internet cable for analysis in LabVIEW platform. Different types of faults are applied at different locations of the transmission line and NI based PMU captures the data for further analysis. Detection of the fault is carried out with the help of FFT coefficients, Parks transformation and Clarke transformation of three phase voltage and current phasors obtained from NI based PMU.

A. *Detection of Fault using FFT*

Real-time three phase voltage and current phasor are acquired from NI based PMU. These phasors are then transformed into fictitious quadrature-phase using Clarke transformation as shown in equation (1) and (2), then to direct and quadrature components using Parks' transformation as shown in equation (3) to equation (5). Equivalent voltage phasor angle (EVPA) and equivalent current phasor angle (ECPA) are computed from equation (6) and equation (7) respectively. FFT analysis has been performed on EVPA and ECPA for detecting the fault as shown in Fig. 5. The detection done on the deviation of EVPA or ECPA coefficient.

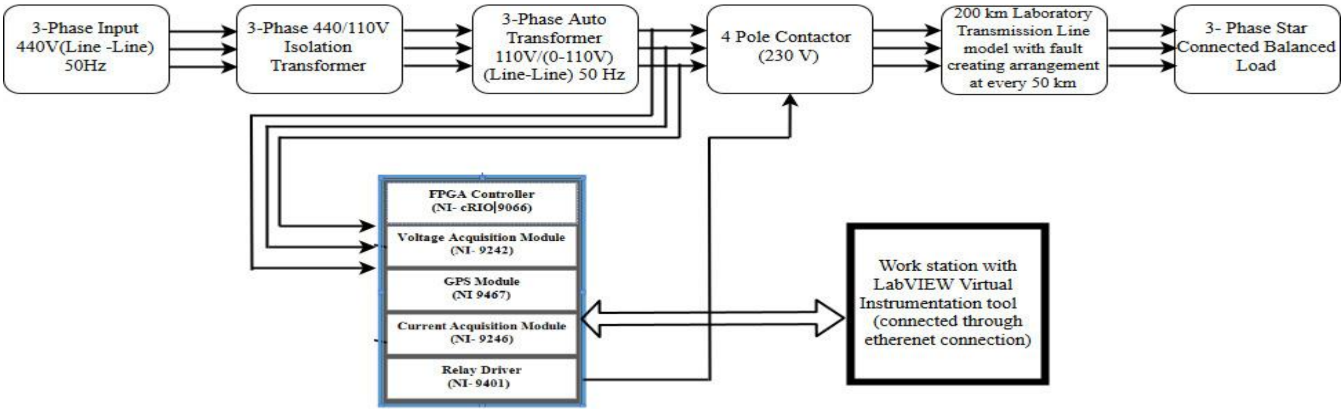

Figure 3. Block diagram of experimental setup

have been performed by using the SVM in LabVIEW platform.

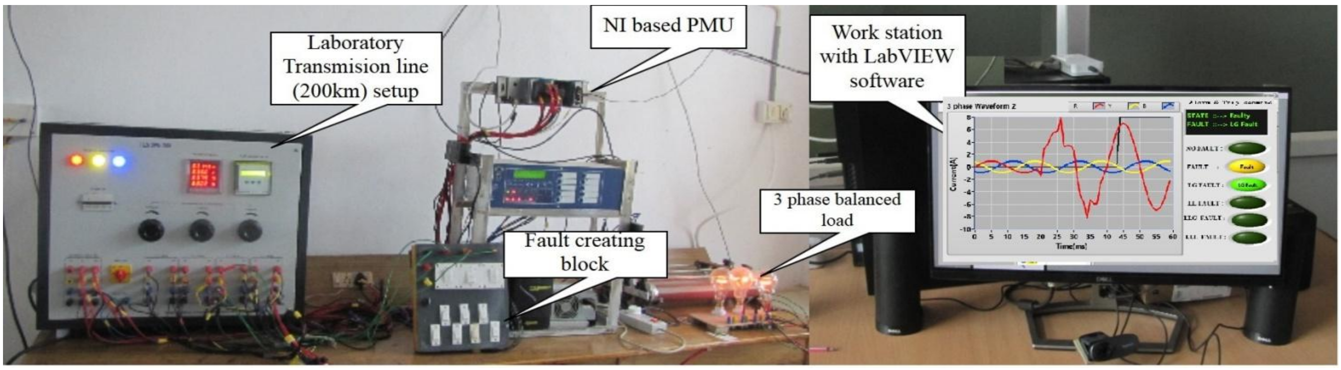

Figure 4. Experimental setup

Table. 1 Transmission Line and Load Specifications

Scale factor	Potential transformer (PT) ratio	1:4
	Current Transformer (CT) ratio	1:1
Line parameter (π -Section)	Resistance	0.2 Ω
	Inductance	8.4mH
	Capacitance (C/2)	2 μF

Load	Resistive load	1K Ω ,300V,1.2A
	Lamp load	230V, 200W

$$\begin{bmatrix} V_\alpha \\ V_\beta \end{bmatrix} = \left[Clarkematrix \right] \times \begin{bmatrix} V_R \\ V_Y \\ V_B \end{bmatrix} \text{......................}(1)$$

$$\left[Clarkematrix \right] = \frac{2}{3} \times \begin{bmatrix} 1 & -\frac{1}{2} & \frac{-1}{2} \\ 0 & \frac{\sqrt{3}}{2} & \frac{-\sqrt{3}}{2} \end{bmatrix} \text{..........}(2)$$

$$\begin{bmatrix} V_{ds} \\ V_{qs} \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \times \begin{bmatrix} V_\alpha \\ V_\beta \end{bmatrix} \text{...................}(3)$$

$$\begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix} = \left[Clarkematrix \right] \times \begin{bmatrix} I_R \\ I_Y \\ I_B \end{bmatrix} \text{......................}(4)$$

$$\begin{bmatrix} I_{ds} \\ I_{qs} \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \times \begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix} \text{....................}(5)$$

$$\text{EVPA}\,(\varphi_{ev}) = \tan^{-1}\left(\frac{V_{qs}}{V_{ds}} \right) \text{....}(6)$$

$$\text{ECPA}\;(\varphi_{ei}) = \tan^{-1}\left(\frac{I_{qs}}{I_{ds}} \right) \text{...}(7)$$

$$\Delta = \left(\frac{1}{N} \right) \sum_{k=0}^{N-1} \cdot \sum_{n=0}^{N-1} \varphi_{ev}(n).e^{\frac{-2\pi nk}{N}} \text{........}(8)$$

$$\Psi = \left(\frac{1}{N} \right) \sum_{k=0}^{N-1} \cdot \sum_{n=0}^{N-1} \varphi_{ei}(n).e^{\frac{-2\pi nk}{N}} \text{........}(9)$$

where Δ and Ψ presents the FFT of the EVPA and ECPA. Where V_R, V_Y, V_B and I_R, I_Y, I_B represents shows the FFT coefficients of EVPA of few samples when different types of the faults are applied on the transmission line.

B. *Fault Classification and Localization Using Support Vector Machine*

Classification and localization of fault is achieved using support vector machine (SVM). As more than two types of faults are involved, the multi class SVM is employed for fault classification. The algorithm is depicted in two stages and its flowchart is shown in Fig. 6. The first stage is learning stage where the model is trained with known data acquired real time by applying predetermined faults. In the second stage, i.e., evaluation stage (prediction stage), the trained model is utilized to classify the type of the fault based on the PMU data acquired in the real-time. The learning and prediction stages are described as follows.

Step 1: (Learning stage)

- The EVPA FFT coefficients $(\Delta_0, \Delta_{50}, \Delta_{100}, \Delta_{150}, \Delta_{200})$ at different harmonic frequencies obtained from equation (8) for 0, 50, 100,150 and 200 Hz with the known fault type (class) as per table 2 and prepared the data set to train the machine learning algorithm.
- Data preparation using Normalization technique.
- Initialize the parameters for the machine learning algorithm (Support Vector Machine).
- Train the model with EVPA FFT coefficient with known fault class. Save the trained model.

Step 2: (Prediction stage)

- Acquiring the real-time 3 phase voltage from NI based PMU
- Evaluate EVPA and calculate the FFT coefficients $(\Delta_0, \Delta_{50}, \Delta_{100}, \Delta_{150}, \Delta_{200})$ for fundamental and harmonic components of online voltage phasor.
- Deploy features in manipulation model

Then the classification model is deployed for predicting the class level.

IV. RESULTS AND DISCUSSION

The first five columns of Table 2 represent the FFT coefficients of the EVPA at different frequencies and the last column represents the respective fault classes. Table 3 shows the respective fault class corresponds to type of fault.

Fig. 6 (a) shows the flow chart of the training with the known data. Fig. 6 (b) shows the fault classification algorithm. The trained model is used to predict the fault from the real-time data captured by PMU.

$\Delta(\Delta_0, \Delta_{50}, \Delta_{100}, \Delta_{150}, \Delta_{200})$ and $\Psi(\Psi_0, \Psi_{50}, \Psi_{100}, \Psi_{150}, \Psi_{200})$ are the FFT coefficients at 0, 50, 100, 150, and 200 Hz and are shown in Table 2.

It can be observed from the Table 2 that during the normal operating condition, the coefficients are not varying. But when the fault is applied, the coefficients are undergoing variation in pre-fault and post fault condition. Thus, the real-time fault detection can be achieved by monitoring these variations.

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Table 2 FFT coefficients of EVPA result

0Hz Δ_0	50Hz Δ_{50}	100Hz Δ_{100}	150Hz Δ_{150}	200Hz Δ_{200}	Fault Classification
0.014	0.003	0.002	0.002	0.002	1
0.011	0.002	0.002	0.002	0.001	1
0.012	0.003	0.002	0.002	0.002	1
0.012	0.003	0.002	0.002	0.002	1
0.012	0.003	0.002	0.002	0.002	1
0.013	0.003	0.002	0.002	0.002	1
0.013	0.003	0.002	0.002	0.002	1
0.012	0.003	0.002	0.002	0.002	1
0.013	0.003	0.002	0.002	0.002	1
0.027	0.006	0.004	0.004	0.004	2
0.089	0.02	0.014	0.012	0.012	2
0.066	0.015	0.01	0.009	0.009	2
0.026	0.006	0.004	0.004	0.003	2
0.085	0.02	0.013	0.012	0.011	2
0.104	0.024	0.016	0.014	0.014	2
0.049	0.011	0.008	0.007	0.006	2
0.115	0.026	0.018	0.016	0.015	2
0.055	0.013	0.009	0.008	0.007	2
0.306	0.07	0.048	0.042	0.04	2
0.91	0.209	0.144	0.126	0.119	2
0.353	0.081	0.056	0.049	0.046	2
0.124	0.029	0.02	0.017	0.016	2
0.507	0.116	0.08	0.07	0.066	3
0.594	0.136	0.094	0.082	0.078	3
0.051	0.012	0.008	0.007	0.007	3
0.723	0.166	0.114	0.1	0.094	3
0.714	0.164	0.113	0.099	0.093	3
0.461	0.106	0.073	0.064	0.06	3
0.761	0.174	0.12	0.105	0.099	3
0.522	0.12	0.082	0.072	0.068	3
0.842	0.193	0.133	0.116	0.11	4
0.981	0.225	0.155	0.135	0.128	4
0.979	0.225	0.154	0.135	0.128	4
0.847	0.194	0.134	0.117	0.111	4
0.771	0.177	0.122	0.106	0.101	4
1.183	1.162	0.031	0.014	0.0011	5
1.178	0.16	0.028	0.011	0.00017	5
1.171	0.154	0.022	0.008	0.009	5
1.168	0.15	0.019	0.006	0.0007	5

The LabVIEW output of the machine learning algorithm is presented in fig. 7. The LabVIEW program block diagram is shown in Fig. 8. For better clarity the block diagrams are shown in three parts as Fig. 8 (a), (b) and (c). The location of fault is calculated by making use of the current phasors acquired from NI based PMU. Table 4 shows the FFT coefficients of ECPA calculated from a few samples, when different types of faults are applied at different locations of transmission line. The variation in these values indicate the existence of the fault. Once the fault is detected, the SVM algorithm predicts the as per Fig. 9.Fig. 9(a) shows the learning stage and Fig. 9(b) for predicting stage.

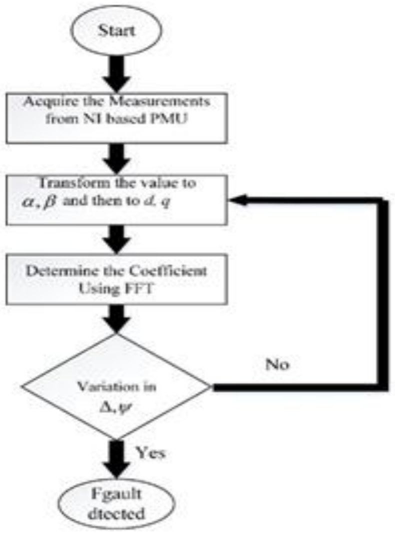


Figure 5. Fault detection algorithm

As the line impedance varies with the occurrence of the fault, the current flowing in the line fluctuates, thereby changing its ECPA.

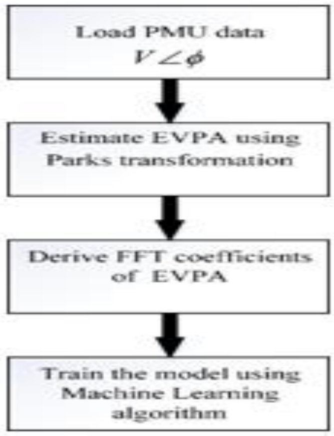
Table 3. Fault classification

Classification	Fault type
1	No fault
2	LG Fault
3	LL Fault
4	LLG Fault
5	LLL Fault

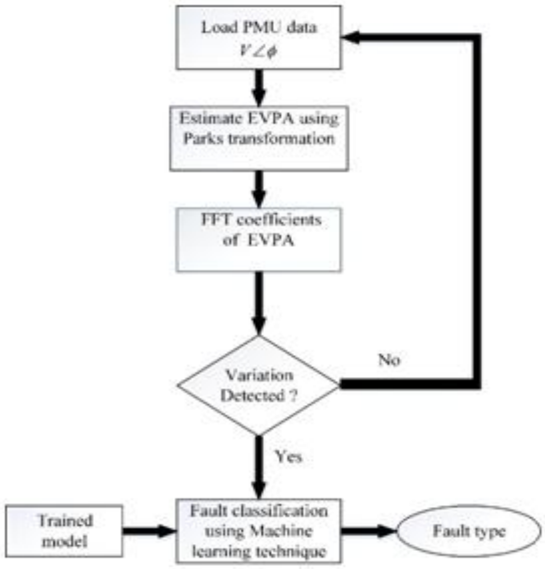
The variation of ECPA is detected by examining it FFT coefficients $(\Psi_0, \Psi_{50}, \Psi_{100}, \Psi_{150}, \Psi_{200})$ at different fundamental frequency (50Hz) and harmonic frequencies (0, 100, 150 and 200 Hz) of the three phase signal.

Apart from fault detection, classification and localization on the transmission line, this study also addresses the protection of transmission line. For the demonstration purpose, a solid state based relay is employed in the transmission line experimental setup. These relays are driven by NI 9401 relay driver module.

Once the fault is detected, tripping signal is generated and fed to the relay module to protect the faulty line. When the fault is cleared, the relay driver module sends the reclosing signal. organizational editing before)



(a)



(b)

Figure 6. Fault classification algorithm (a) Learning stage (b) Prediction stage.

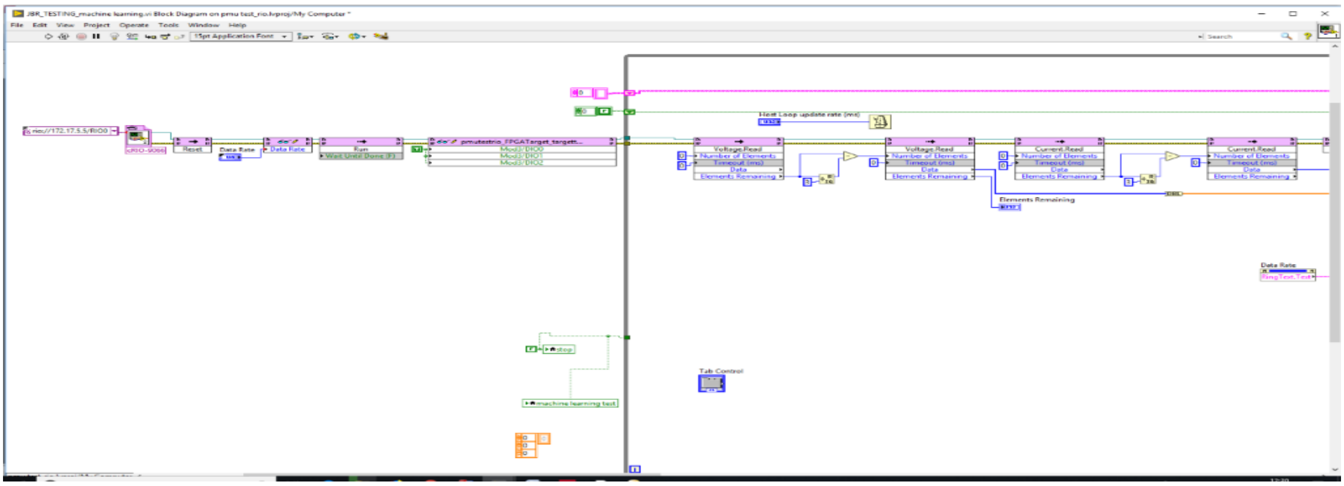
Table 4. FFT coefficient of the ECPA result

Fault type	FFT coefficient of ECPA at different location				
LG Fault	Ψ_0	Ψ_{50}	Ψ_{100}	Ψ_{150}	Ψ_{200}
No fault	1.087232	0.249348	0.171551	0.150116	0.142072

50km	0.8245	0.189083	0.130083	0.113958	0.107708
100km	0.75265	0.17255	0.11885	0.103925	0.098325
150km	0.776	0.178889	0.122571	0.107143	0.101381
200km	0.9338	0.2142	0.1474	0.1289	0.12225
LL Fault	Ψ_0	Ψ_{50}	Ψ_{100}	Ψ_{150}	Ψ_{200}
No fault	1.087232	0.249348	0.171551	0.150116	0.142072
50km	1.166435	0.267435	0.184	0.16113	0.152435
100km	0.89214	0.204571	0.140786	0.123179	0.116536
150km	0.748692	0.17159	0.118128	0.103333	0.097897
200km	0.9647	0.221233	0.1522	0.133167	0.126067
LLG	Ψ_0	Ψ_{50}	Ψ_{100}	Ψ_{150}	Ψ_{200}
No fault	1.087232	0.249348	0.171551	0.150116	0.142072
50km	0.650975	0.14925	0.102675	0.089925	0.085025
100km	0.876431	0.201017	0.138328	0.121017	0.114603
150km	0.78984	0.18116	0.12468	0.10908	0.10324
200km	0.92404	0.21194	0.1458	0.1276	0.12068
LLL	Ψ_0	Ψ_{50}	Ψ_{100}	Ψ_{150}	Ψ_{200}
No fault	1.087232	0.249348	0.171551	0.150116	0.142072
50km	0.761904	0.174654	0.120288	0.105231	0.099615
100km	0.752098	0.172561	0.111866	0.10378	0.098195
150km	0.7038	0.1614	0.111086	0.097171	0.091914
200km	0.817909	0.187545	0.129159	0.112977	0.106864

Table 5. Comprison of results of Proposed algorithm and SEL-311C

S. No.	Test FFT coeff.	0HZ (0f)	50 HZ (1f)	100HZ (2f)	150HZ (3f)	200HZ (4f)	Predicted fault type	Actual fault type (SEL-311C)
1	Test-1	0.015	0.001	0.002	0.003	0.002	No fault	No fault
2	Test-2	0.088	0.03	0.0131	0.0122	0.012	LG	AG
3	Test-3	0.465	0.105	0.075	0.065	0.05	LL	BC
4	Test-4	1.2001	0.155	0.0189	0.005	0.0007	LLG	ABG
5	Test-5	0.98002	0.2242	0.1565	0.1352	0.128	LLL	ABC



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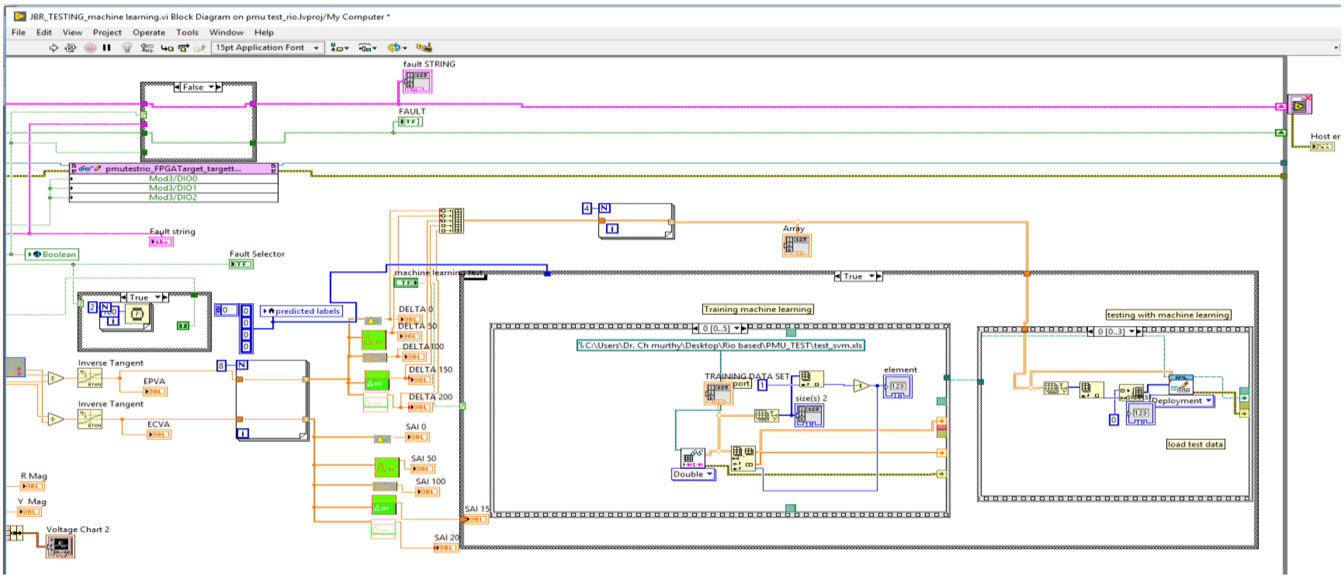

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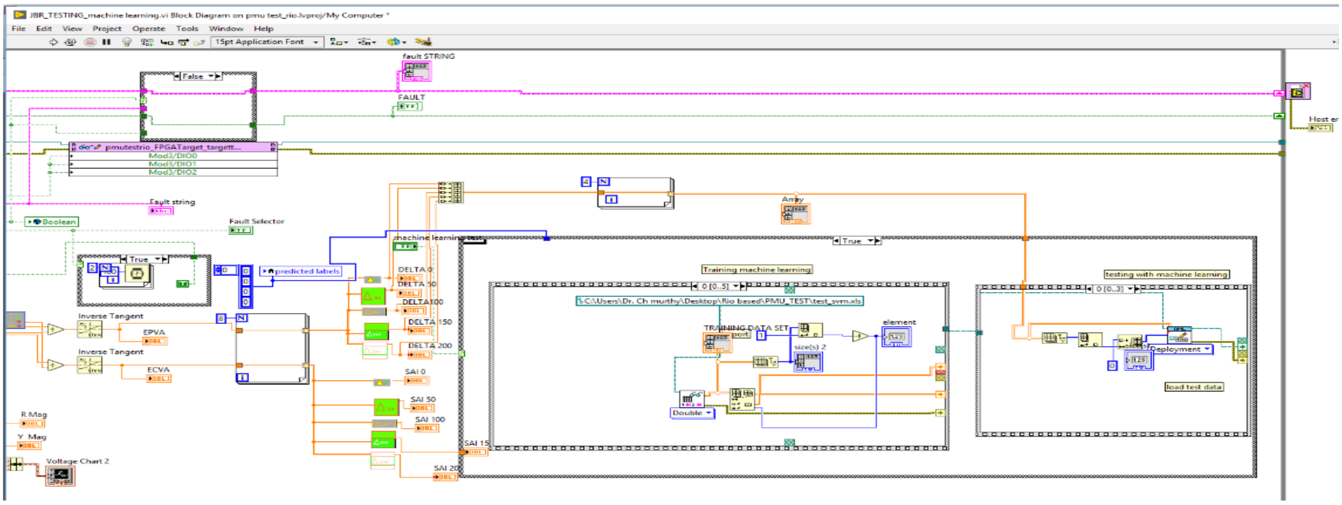
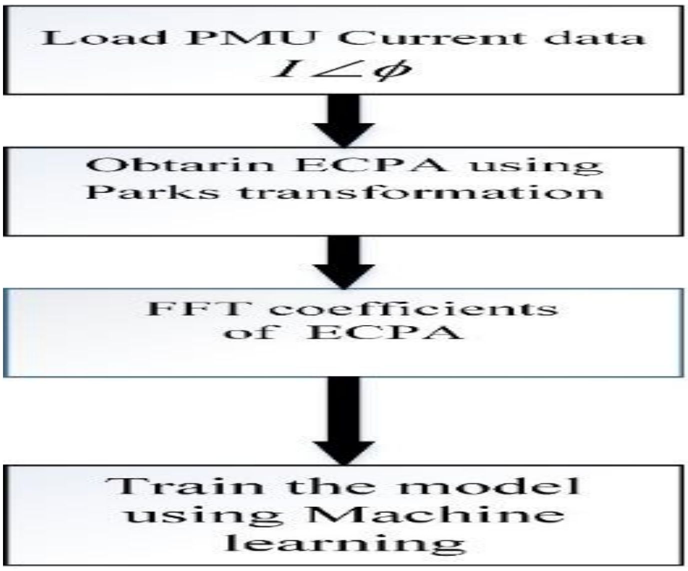


(c)

Figure 8 (a)-(c): LabVIEW program for fault location



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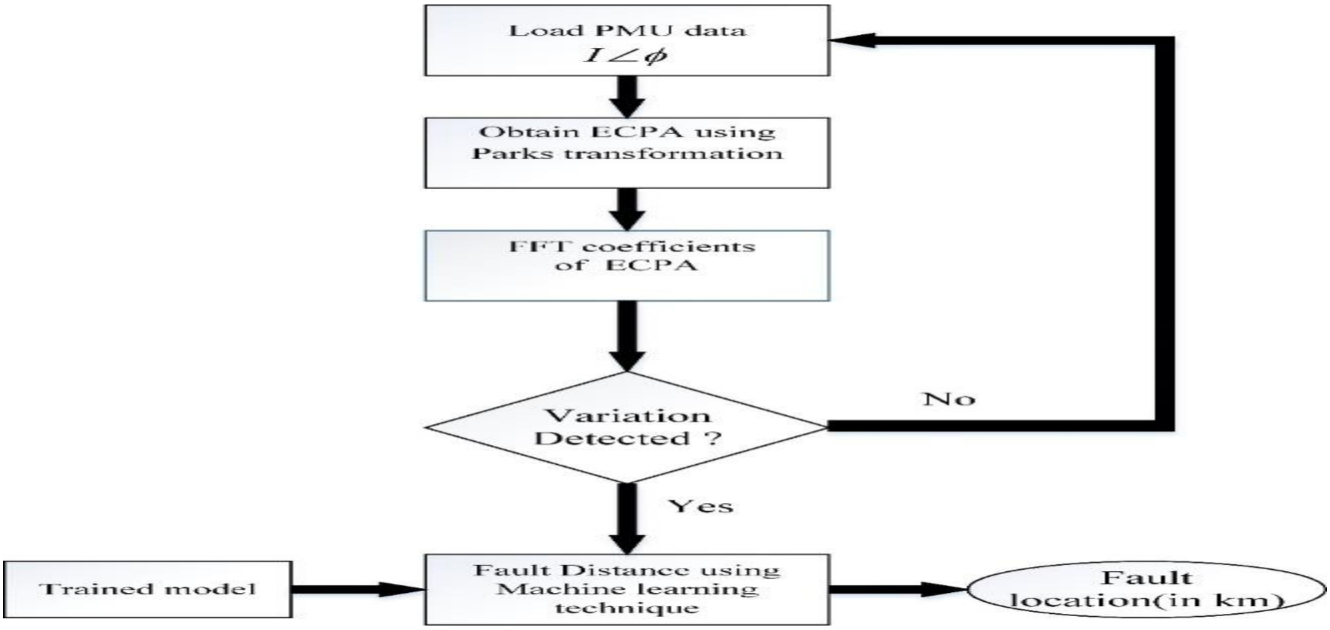

(b)

Figure. 9 Fault localization algorithm (a) Learning stage (b) Prediction stage algorithm

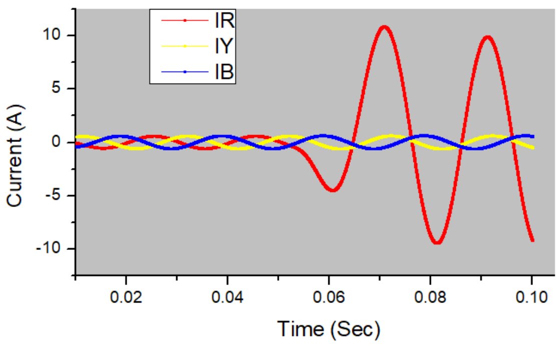

Figure. 10 Current waveforms under LG fault

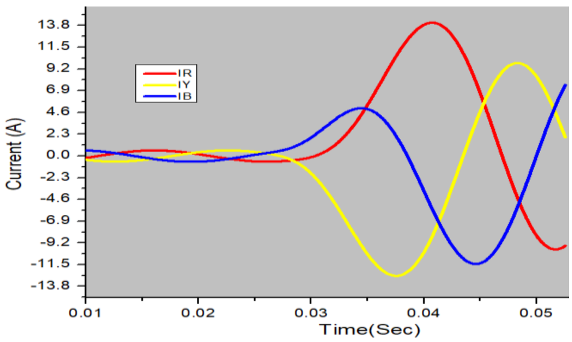

Figure. 13 Current waveforms of LLL fault

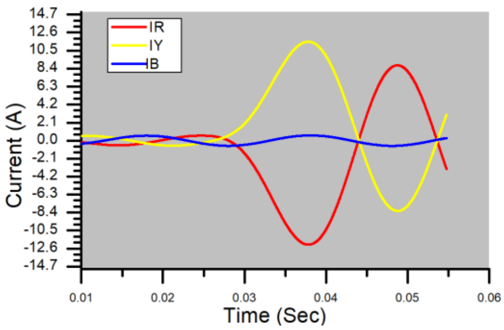

Figure 11. Current waveform under LL fault

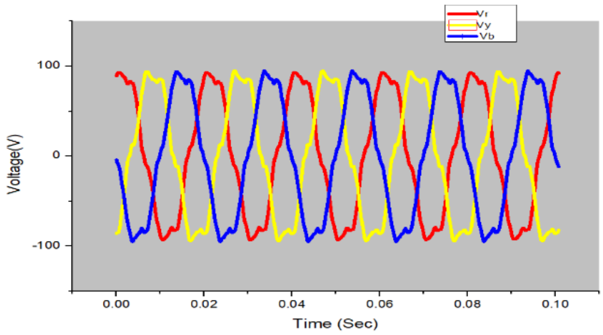

Figure .14 Voltage waveform under no fault condition

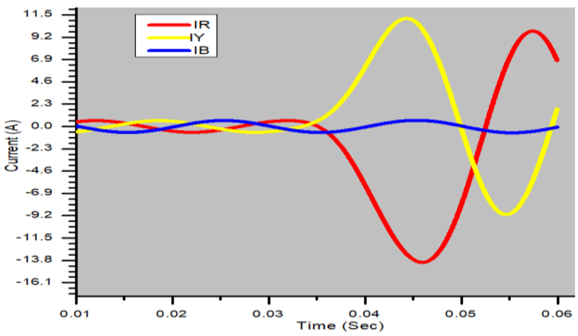

Figure. 12 Current waveforms under LLG fault

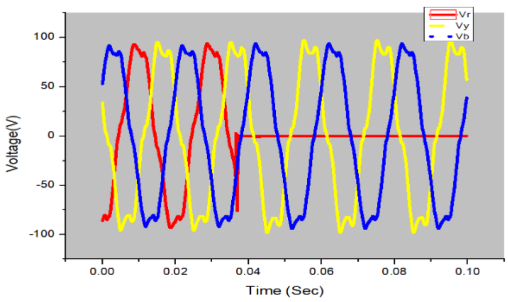

Figure .15 Voltage waveform under LG fault

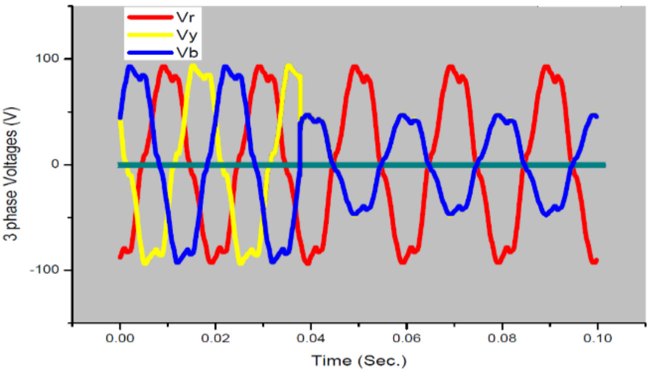

Figure. 16 Voltage waveform under LL fault

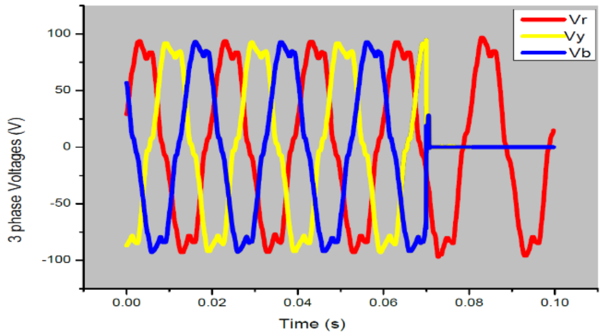

Figure. 17 Voltage waveform under LLG fault

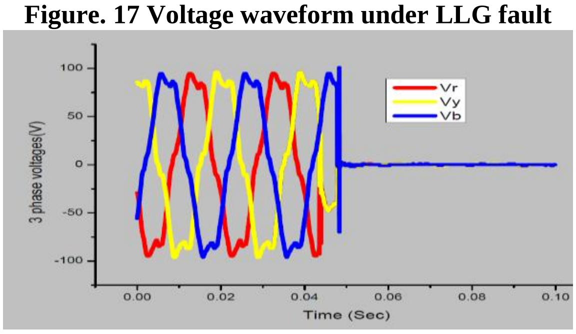

Figure. 18 Voltage waveform under LLL fault

Table 6. Comparison of fault classification results with LR and NN

Fault type	SVM	LR	NN
LG	**0%**	**5%**	**3%**
LL	**0%**	**7%**	**2%**
LLG	**0.01%**	**3%**	**4%**
LLL	**0%**	**8%**	**5%**

Table 7. Comparison of LG fault result at different location

Classifier	50 km	100 km	150 km	200 km
LR	**2%**	**4%**	**6%**	**4%**
NN	**5%**	**3%**	**1%**	**1%**
SVM	**0%**	**0.01%**	**0**	**0%**

Table 8. Comparison of LL fault result at different location

Classifier	50 km	100km	150 km	200km
LR	**3%**	**5%**	**5%**	**3%**
NN	**1%**	**2%**	**1%**	**2%**
SVM	**0%**	**0%**	**0%**	**0%**

Table 9. Comparison of LLG fault result at different location

Classifier	50 km	100km	150 km	200km
LR	**5%**	**0%**	**3%**	**5%**
NN	**7%**	**0%**	**2%**	**2.50%**
SVM	**0%**	**0.01%**	**0%**	**0%**

Table 10. Comparison of LLL fault result at different location

Classifier	50 km	100km	150 km	200km
LR	**2%**	**4%**	**3%**	**3%**
NN	**2%**	**2%**	**1%**	**1.20%**
SVM	**0%**	**0%**	**0%**	**0%**

V. CONCLUSION

The fault detection, classification and localization using FFT and SVM is found to be efficient, faster and reliable for enhancing situational awareness in transmission line using NI based PMU. Further, the protection can be provided using the relay module with the cRIO to isolate the faulty line and protect the rest of the transmission line. The advantages of using LabVIEW software which is equipped with real-time data acquisition makes the proposed laboratory setup resembling the real transmission line by incorporating appropriate changes.

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