A Methodology for Fault Detection and Classification using PMU Measurements

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***Abstract*—Phasor Measurement Units (PMU) has become integral part of advanced measurement technologies for power transmission and distribution systems. The PMU measurement gives a clear picture of sequence of phenomenon happening in power system. In power system, faults, load change etc. happens frequently. Since faults are severe cases it is required to detect them at the earliest. Here a two-stage fault detection method is proposed which can clearly distinguish between disturbances and faults in power system. The positive and zero sequence voltages obtained from PMUs are utilized in the detection algorithm. Once the fault is detected, it is required to recognize the kind of fault that has occurred. A Support Vector Machine is proposed for categorizing the fault type. The 14 bus IEEE transmission test system is modelled in PSS/E and MATLAB/Simulink for testing and validating the proposed detection and classification methods.**

***Index Terms*—Fault location and classification, Phasor Measurement Units (PMU), P-V Analysis, Support Vector Machine (SVM)**

I. Introduction

ELECTRIC power networks around the world are being modified to smart power grids (SPGs) by integrating advanced methods to keep a track of events in power systems and also by incorporating advanced control methods [1], [2]. The modern data acquiring technology, like PMUs, has become an integral part of smart power systems. PMUs keep a track of transmission system events over large areas in order to detect and further prevent instabilities in grid [2], [3]. Advanced monitoring of transmission and distribution systems, essentially requires new technologies for measurement, and PMUs are latest of that category [4]. The measurements from PMUs (i.e. current, voltage, frequency etc.) placed at optimal locations in the power systems are sent to control center. Phasor data concentrator (PDC) is used to store these data in hierarchical structure at the control centers [5], [6]. Using Global Positioning System (GPS) receivers the quantities measured are time-synchronized [7]. PMUs make it possible to accurately monitor grid dynamics in real time [8], [9]. From the data obtained from PMUs, one can interpret the series of events that have caused the ruinous behavior of power system. The theory of phasor can be applied in analysis of any sinusoidal system with a nominal frequency, thus we can apply it to power systems. The estimation of synchrophasors is based on the concept of phasors. Taking Co-ordinated Universal Time (UTC) as reference the phase-angles are calculated [10]. Therefore, for all the measured sinusoidal signals in wide area will have a distinctive reference. Therefore the synchrophasors, received from different location in a power network, are time-stamped and can be compared, i.e. the time dissemination rely on satellite systems. Various research works are being carried out in analysis of PMU data.

The disturbances in power system cannot be wholly avoided. More time it takes to identify and mitigate the fault, more destruction may result in the electrical power system, especially during peak loads, which could lead to the disintegration of the system, causing the power outage or disturbance to spread into larger parts, resulting in prolonged exposure of the electrical network to faults. It is essential to detect fault, its type and localise it. Incorporating PMU for this purpose is an area of ongoing research. The impedance measurement-based method used for detecting, classifying and localizing the fault is one of conventional method. Travelling wave method are also widely used [11]. PMUs are now being progressively used to sense transmission lines faults [1]. An impedance based fault area/ location in transmission line using PMU data is presented in [12]. Here PMUs are installed on both ends (sending and receiving) of the transmission line. This technique can also be used for transmission lines with multi-terminal. By installing PMU on both sides of transmission line, we can get synchronized voltage and current phasor. A method of detecting and estimating location of fault using this PMU data is implemented in [13]. A differentiation between no-fault and faulted condition is very important. Taking this into consideration, an adaptive fault location/detection algorithm using PMU data is proposed in [14], [15]. A method of detecting, classifying and localising transmission fault using Phasor measurement data and Equivalent phasor angle is proposed in [16]. A comparison of Wavelet and Fourier transform for classifying faults in transmission line is discussed in [17]. A method of detecting and classifying faults in transmission line using PMU data only from generator bus is discussed in [18].A fault detection method which utilizes predefined volt-

978-1-5386-6159-8/18/$31.00 © 2018 IEEE

age threshold values for various fault conditions is discussed in [19]. Artificial intelligence/Machine learning techniques are now being used for fault analysis i.e. detection, identification, localisation of faults in power transmission systems. In [16] a multiclass SVM is used for identifying the type of fault and its location. In [20] the application of synchronized phasor measurement is detailed. The use of machine learning methods like clustering and classification are also discussed.

In this paper, fault detection and classification methods using measurements from PMU are proposed. PMUs are placed at optimal location in the transmission test system. A fault detection method is proposed using positive and zero sequence voltage measurements obtained from PMUs. This method can distinguish between faults and other disturbances/changes occurring in power systems. Once the fault is detected, the next important step is to determine the type of fault that has occurred. For this purpose an SVM has been proposed. The advantage of this method is that the input to SVM is measurements from a PMU. This PMU is placed at a generator bus. The paper is organized as follows. The proposed two-stage fault detection method is discussed in Section II. The proposed SVM used for identifying the type of faults is explained in Section III. The proposed fault detection and classification algorithms are tested and validated on 14 bus IEEE test system and results are discussed in Section IV.

II. Fault Detection Method

Fault detection algorithm discussed here is a two stage detection method, and uses the data acquired from the optimal PMU locations. The response time of the algorithm for the proposed methodology in this case is almost instantaneous as it does not contain any loop. The discrimination between the faults and other disturbances/changes can be distinguished by using the available positive and zero sequence voltage measurements. The first stage of this algorithm is used to distinguish major phase faults and the second stage is used for the sensitive cases. The methodology requires the following steps.

A. Obtain the positive and zero seq. measurements from the PMUs

The proposed methodology uses the measurements available from the PMU placed at the optimal locations. Optimal locations are chosen based on the observability of the system. Bus-2, bus-6, bus-7 and bus-9 are the optimal locations for the system from which we can get the positive and zero sequence measurements of current and voltage directly from PMU. The data is received from PMU at rate of 50 frames/sec.

B. Find the Voltage knee point from P-V curve analysis

Typically a voltage collapse at a bus occurs due to various reasons like switching on heavy load, faults and/or has reactive power shortage. Most of the events in the power systems that cause voltage collapse, which are not as severe as a fault will cause, can be considered as similar to switching on heavy load. For our analysis purpose, i.e. to discriminate between a fault and other disturbances, it is required to analyze the possible voltage deviation in a system form the critical load change case, hence this voltage deviation can be used as a threshold to distinguish between a severe fault and other disturbances/ changes. So PV curve analysis method is adopted to find the voltage threshold. Generally this method is used for voltage stability of a radial or meshed network [21].

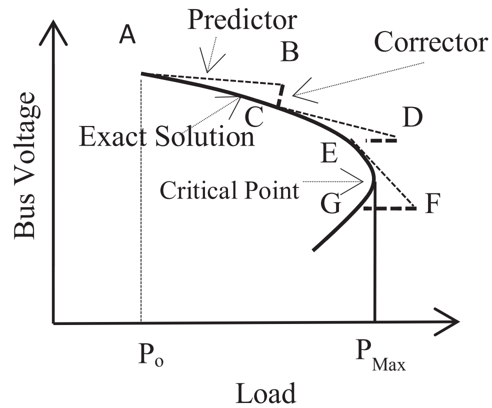

Fig. 1. P-V Curve

1) PV curve analysis: To construct a PV curve, base case load flow result is required. This result is further used for continuation load flow analysis involving predictor and corrector steps. Predictor step uses the base load flow case to predict the specified load increase pattern. The corrector step provides a definite correction using conventional load flow analysis by keeping the predicted overall load change of the system fixed. This iterative process continues till the load change is beyond the maximum load, where the load flow wouldn't converge with the corresponding corrector step. To know the exact maximum load, the load increase step size during the predictor step should be reduced gradually. Fig. 1 shows the P-V curve giving the maximum load.

Rescheduled generation with the increased load is expressed using a reformulated power flow equation as shown in (1).

$$F(\theta, V) = \lambda K \tag{1}$$

Where
λ : Load parameter
θ : Bus voltage angle
V : Bus voltage magnitude
K : Percentage of load change at each bus
For each step of the load change, λ, whose range lies as shown below, the reformulated power flow equations have to be solved until the knee point is reached.

$$0 \leq \lambda \leq \lambda_{critical}$$

λ= 0 for base case corresponds to P_0 and $\lambda = \lambda_{critical}$ for critical load corresponds P_{Max} in Figure 1.

C. Positive sequence voltage threshold and zero sequence voltage

In the proposed two stage algorithm for fault detection, in the first stage, the positive sequence voltage deviation of each PMU observed bus is required. The bus having maximum voltage deviation is taken for the comparison with its set threshold value, which is based on the PV curve analysis. This method can filter out the severe fault cases like phase faults with the load change case (as the threshold is chosen by considering the systems worst case scenario due to load change). In some earth fault cases, which generally occur in the middle of the transmission line, this method is less accurate or may not work because the voltage deviation is less, which may appear like a load change. Hence to distinguish this, it is required to investigate further, i.e. the second stage of the algorithm by comparing with zero sequence voltage deviation with its set value. The detailed flow chart for the algorithm is given in Fig 2. In Fig 2, $\Delta V_{i(PMU)}$ and $\Delta V_{0i(PMU)}$ are positive sequence and zero sequence voltage deviation observed at bus 2, 6, 7, 9 ($i = BusNo.$) respectively. $V_{ipre-dist}$, $V_{0ipre-dist}$ are value of positive sequence and zero sequence of voltage before disturbance respectively. V_{idist} is the voltage during the disturbance. $\Delta V_{i(TH)}$, $\Delta V_{0i(TH)}$ are the positive and zero sequence threshold values obtained after analysis.

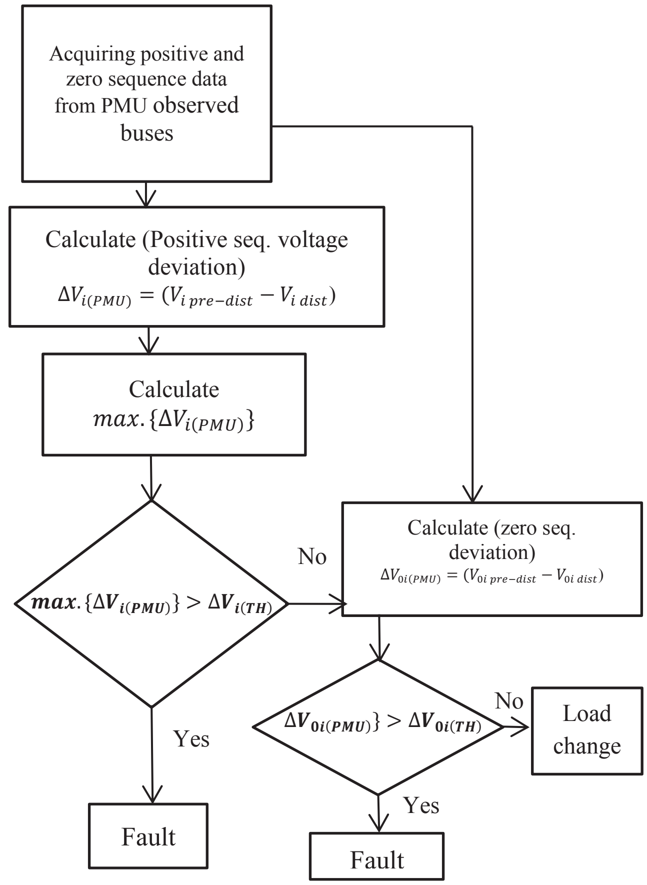

Fig. 2. Flow chart of proposed two-stage fault detection method

III. Fault Classification

The transmission line faults are successfully detected using the two-stage fault detection method. The next significant part is to classify/categorize various phase and earth faults in power systems. From PMU, we get relevant measurements like phasors, positive, negative, zero sequence of voltage and current. Here a SVM is proposed which utilizes the measurements obtained directly from PMUs. It also utilizes the measurements only from one bus to classify the fault type. The proposed SVM is explained below.

A. Support Vector Machine

Supervised learning algorithms like SVM are used for classification and regression analysis. As well as this can be used for data classification from a linear and non –linear data set. The kernel trick enables the SVMs to efficiently perform a non-linear classification, by completely mapping its inputs into feature spaces which is high-dimensional. Hava Siegelmann and Vladimir Vapnik developed the support vector clustering [22] algorithm, which is considered as most popular clustering algorithm for industrial applications. It applies the statistics of support vectors. These vectors are used to categorize unlabeled data, in the support vector machines algorithm. Support vector decides the decision boundary, i.e., a hyperplane (for two classes) or set of hyperplanes (for multi-class) in a space which is high- dimensional or infinite-dimensional. It can also be used for regression and also for outlier detection [23]. In SVM classifier, a good distinction of any class is achieved when the hyperplane has the maximum functional margin. Functional margin is the largest perpendicular distance to the closest point in the training set. Larger the margin, higher is the classification accuracy.

B. The proposed SVM

The proposed SVM uses measurements directly obtained from PMUs to classify the type of faults. Once the fault is detected, it would be necessary to identify what type of fault has happened. The RMS values of voltages and the zero sequence current are the data used to train the SVM. The main advantage of this proposed classification method is that data from only one bus is required and also it utilizes measurements obtained directly from PMU. The zero sequence current is present only for earth fault in power system.

The SVM is developed in Python environment. It has scikit-learn library for implementing machine learning algorithms. Scikit-learn library have structures, i.e. object creation, prediction and fitting model. Tuning the values of parameters for machine learning algorithms reasonably improves the performance of the model. The important parameters of an SVM are regularization parameter C, kernel and gamma.

A standard radial Gaussian kernel or Radial Basis Function kernel (RBF) is expressed as in (2).

$$k(x,y) = e^{\left(-\dfrac{\gamma\|x-y\|^2}{2\sigma^2}\right)} \tag{2}$$

In equation (2), k is the kernel, x is point in data set, y is landmark point. The deviation between the data point and landmark point is the basis of classification. The bandwidth parameter λ is the only kernel parameter. The fixed parameter σ plays a role in determining the boundary. Other kernels are linear, polynomial, sigmoid and others. The parameter gamma determines how to fit data as per training data set. Over-fitting problem may result as value of gamma increases. SVM works efficiently with distinct margin for separation. It is found to be effective even in high dimensional spaces.

IV. Results and Discussions

A. Case study

For validating the proposed methodology for fault detection and classification, a case study with modified IEEE 14 bus system is considered with system voltage of 220kV and frequency 50 Hz. The system is modelled in MATLAB and PSS/E with the transmission line parameters as per the data given in pu. The following generator ratings are considered for this study: Gen. 1 connected to bus 1, having a rating of 615MVA, base case generation is 232.4MW and -16.54MVar; Gen. 2 connected to bus 2, having a rating of 100MVA, base case generation of 40MW, 43.55MVar; Gen. 3 (Syn. Condenser) connected to bus 3, having rating of 40MVA, base case generation of 25.07MVar; Gen. 4(Syn. Condenser) connected to bus 6, having a rating of 25MVA, base case generation of 12.73MVar; Gen. 5 (Syn. Condenser) connected to bus 8, having a rating of 25MVA, base case generation, 17.62MVar.

B. Fault Detection

Initial step of the fault detection method is to set the threshold values of positive sequence voltage deviation and zero sequence voltage deviation threshold. As discussed in the methodology section, to set the threshold for positive sequence voltage deviation, PV analysis is required with the worst case load change scenario considered. To observe this, the PV analysis tool of PSS/E software is used. Here different scenarios of load change combinations are observed and it is found that the load increment up to 300MW in steps of 100MW with fixed pf at bus 2 causes a maximum voltage collapse at the PMU observed buses. The Positive voltage deviation observed using PV analysis in PSS/E are $\Delta V_2 = 0.257pu$, $\Delta V_6 = 0.205pu$, $\Delta V_7 = 0.217pu$, $\Delta V_9 = 0.257pu$. The P-V curve of test system is given in Fig. 3. These load changes are also simulated in MATLAB Simulink, which were found $\Delta V_{2(TH)} = 0.295pu$, $\Delta V_{6(TH)} = 0.239pu$, $\Delta V_{7(TH)} = 0.241pu$, $\Delta V_{9(TH)} = 0.240pu$. As the different disturbance scenarios are created in MATLAB Simulink, the thresholds are chosen, obtained from the same software environment. The zero sequence thresholds are chosen 0.05pu for all PMU observed buses based on the observations. Validation of the algorithm is checked by creating numerous fault cases at different locations in the test system at time 0.35sec to 0.45sec, the details of the observations are provided in Fig. 4, Fig. 5 and Fig. 6 and Table I. In Fig. 4, a LL and LLL fault is applied at 50% of the transmission line from bus 13 to bus 14. The maximum voltage deviation is observed at PMU bus 6 and compared with deviation threshold of the same bus. It is observed that deviation is greater than threshold.

Table I gives the disturbance identified by the two-stage fault detection method. It is seen that a clear distinction between fault and other disturbances is done successfully.

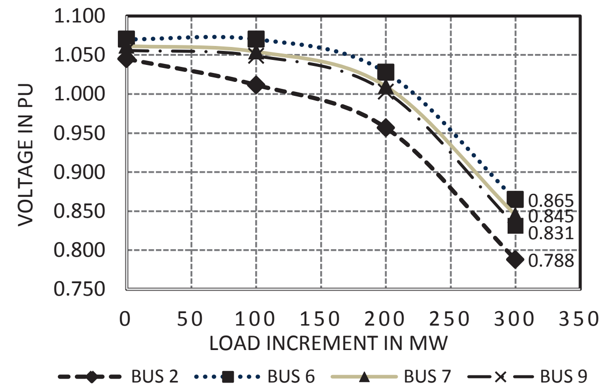

Fig. 3. P-V Curve of Test System (using PSS/E)

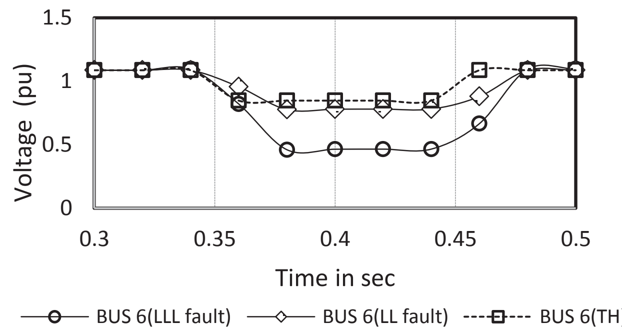

Fig. 4. PMU observation at bus 6 (Phase faults at Trans. line$(13-14)$)

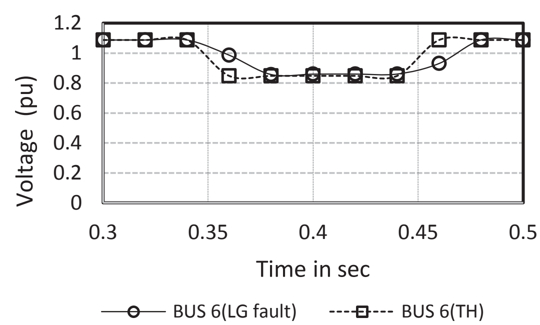

Fig. 5. PMU observation at bus 6 (Earth fault at Trans. line 13-14)

TABLE I
EVENT DETECTION BY FAULT DETECTION METHOD

Event Type	**Positive Seq. Voltage deviation** $max.\Delta V_{i(PMU)}$ **in pu**		**Zero Seq. Voltage deviation** $max.\Delta V_{0i(PMU)}$ **in pu**		**Event detection by proposed *method***
	Deviation	***Detection Location***	***Deviation***	***Detection Location***	
LLL Fault (Tr. line 1-5) 50% from Bus 1	0.744	BUS 6	-	-	Fault
LL Fault (Tr. line 1-5) 90% from Bus 1	0.417	BUS 2	-	-	Fault
LG Fault (Tr.line 13-14) 50% of the line	0.227	BUS 6	0.124	BUS 6	Fault
LLL Fault (Tr.line 10-11) 50% of the line	0.739	BUS 9	-	-	Fault
LLG Fault (Tr.line 10-11) 50% of the line	0.524	BUS 9	-	-	Fault
LG Fault (Tr.line 13-12) 50% of the line	0.25971	BUS 6	-	-	Fault
Disturbance due to load change 200MW, 117.05MVar at bus 2	0.2259	BUS 2	0	-	Other Distur-bances

Positive sequence deviation threshold:
$\Delta V_{2(TH)} = 0.295pu$, $\Delta V_{6(TH)} = 0.239pu$,
$\Delta V_{7(TH)} = 0.241pu$, $\Delta V_{9(TH)} = 0.240pu$
Zero sequence threshold for each bus is 0.05pu

In Fig. 5, LG fault is applied at 50% of the transmission line from bus 13 to 14, maximum deviations is observed at bus 6, which is same as the set threshold. To discriminate it from the load change, the second stage of the algorithm is used. In the second stage, Zero sequence voltage of the same bus is compared with the set threshold value as shown in the Fig. 6 and found it is greater than the threshold; hence it is a fault case.

C. Fault Classification

Here RBF kernel is used in SVM. Around 2100 data points are used to train the SVM. The more data points are used; better boundary for classification is obtained. The data set includes no fault, Line to ground faults (LG), Line to Line faults (LL), Double Line to ground (LLG), and three phase faults (LLL, LLLG) voltage and current measures. Various faults were created at different location in the IEEE 14 test case system and PMU data from generator bus is recorded. The major advantage of this proposed system is that it is a simple SVM, computational time is very less. All the unbalanced faults are classified accurately. Since LLL, LLLG faults are rare power system faults; it is classified into one category, i.e. symmetrical fault. It is found that 99.04% of data are classified correctly. The confusion matrix is also known as an error matrix, which is the result of the proposed SVM, is shown as in Table II. The performance of the SVM is done by evaluating the confusion matrix. Each column and rows of the confusion matrix represents the instances in a predicted class and an actual class respectively. The diagonal elements of the matrix give the correctly predicted values. Here nearly 410 test cases with all types of faults (i.e. Symmetrical faults (SYM), LG faults (RG, YG, BG), LL faults (RY, YB, RB), LLG faults (RYG, RBG, YBG)) and no faults (NF) are classified by the proposed SVM.

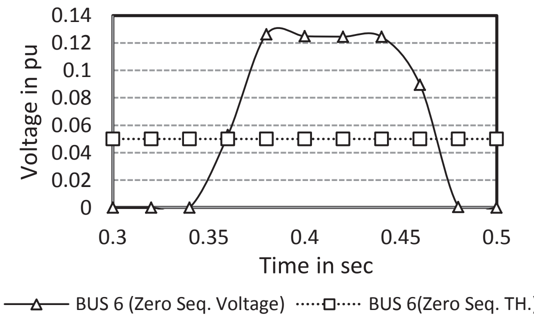

Fig. 6. PMU zero seq. observation at bus 6 (Earth fault at Trans. line 13-14)

TABLE II
CONFUSION MATRIX OF PROPOSED SVM

→ Actual / ↓Predict	SYM	RY	RYG	RB	RBG	RG	YB	YBG	YG	BG	NF
SYM	35	0	0	0	0	0	0	0	0	0	0
RY	0	17	0	0	0	0	0	0	0	0	0
RYG	0	0	24	0	0	0	0	0	0	0	0
RB	0	0	0	15	0	0	0	0	0	0	0
RBG	0	0	0	0	22	0	0	0	0	0	0
RG	0	0	0	0	0	19	0	0	0	0	0
YB	0	0	0	0	0	0	23	0	0	0	0
YBG	0	0	0	0	0	0	0	22	0	0	0
YG	0	0	0	0	0	0	0	0	16	0	0
BG	0	0	0	0	0	0	0	0	0	14	0
NF	0	0	0	0	1	0	1	2	0	0	210

V. Conclusion

Electric power networks are susceptible to various types of faults and disturbances mainly load changes. It is essential to distinguish between power system disturbances and faults. A two-stage fault detection method has been developed. The proposed fault detection method is found to distinguish between power systems disturbances like load change and power systems faults. The proposed algorithm utilizes voltage threshold value obtained by detailed analysis of the test system, which clearly gives the margin between the two scenarios. In those faults which have voltage deviation almost equivalent to set threshold value, the zero sequence voltage thresholds can differentiate the fault and other disturbances cases. After detection of fault an SVM is used to identify/classify the fault type. The SVM has been found to successfully classify the types of fault for a large number of test cases. When there is no fault in the system, the SVM is able to classify these conditions also. The proposed method utilizes the measurement from PMUs, where PMUs are placed at optimal locations. Therefore, an efficient solution to detect and classify the power system faults using PMU measurement data has been developed and validated that will help the utility operators to take better operation/ actions to handle grid disturbances and fault conditions.

Acknowledgment

The authors are highly obliged and would like to acknowledge the support and resources provided by Central Power Research Institute (CPRI), Bangalore, India.

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