Three-Phase Analysis of Power Quality Disturbances and Classification by SVM

Shilpa.R
Associate Professor,Dept. of ECE
VidyaVardhaka College of Engineering
Mysuru, Karnatka

Shruthi S.Prabhu
M.Tech Scholar, Signal Processing
VidyaVardhaka College of Engineering
Mysuru, Karnataka

P. S. Puttaswamy, PhD
Professor and Head of Dept. EEE
P.E.S College of Engineering
Mandya, Karnataka

ABSTRACT
The ephemeral power quality distortions such as voltage swell, harmonics, transients, voltage sag are incrementing every day with the proliferation of number of solid state devices. The technical difficulties like mis-operation, heating are upshots of this and hence identification and classification of the noise become a needful work. The three-phase voltage distortions are decomposed by the Multivariate Empirical Mode algorithm, for identification of its features and Support vector machine is utilized as a classifier. The online real-time, three-phase obtainable data are also tested by the presented approach.

Keywords
Empirical Mode Decomposition, Multivariate Empirical Mode Decomposition, LIBSVM, Octave 3.8.1, Support Vector Machine.

1. INTRODUCTION
A long time back, a brief time power distortion was not at all a problem. However, with the increase in usage of the solid state devices, demands incremented for non-linear loads. Hence, getting a pure, even balanced phase, sustained magnitudes of voltage is a toilsome. The expansive use of non-linear loads in the field of technology has devalued the quality of power. To enhance the quality of power, the detection of short-time distortions becomes a vital task. The technical difficulties like mis-operation, excess heating, devices aging, etc are upshots of the occurrence of the degraded power and to avert these difficulties, the ephemeral voltage disparities like voltage transients, swell, voltage dip and sustained disparities like harmonics are analyzed here.

The obtained features by Multivariate Empirical Mode Decomposition (MEMD) are trained and respective classes are recognized by the Support Vector Machine (SVM). Most of the algorithms are developed based on the univariate data, this algorithm identifies the feature vectors of trivariate that is the three-phase voltage disparities. The beginning location of the fault can be identified by the application of Hilbert transform.

The online accumulated real-time three-phase voltage disparities fault origin are analyzed based on the presented algorithms. The significance of the frequency and time information of power quality disparities plays a vital part in analysis. Many of the approaches are on the univariate data.

The Kalman filter approach uses the residual model and balanced harmonics approaches; both uses decision thresholds to determine the fault fields to segment the voltage wave. But this method is for single phase voltage wave. This has to be applied three times to analyze the three-phase signals. Dynamic Voltage Restorer analyzes the three-phase voltage signals and is capable of identifying the faults in it. The tensor based method identifies the rotation angle to find the existence of the disparities in voltage signals. Around the peak, both methods introduces small segmentation problems. The variance based multivariate method can classify only the trivariate sag signals [1]. Therefore, this method aims to predict the transients, dips, harmonics and swell voltages using a promising, evolving approach called as the MEMD.

2. METHODOLOGY
The basic stages composed of the following stages, Figure.1.

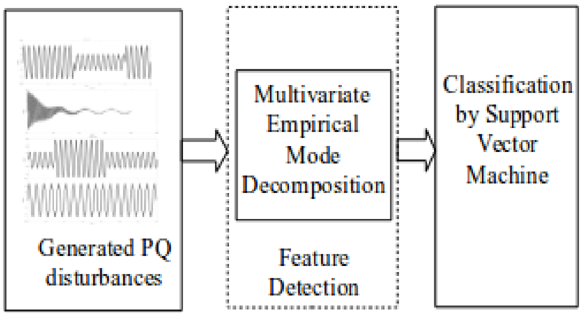


Figure 1. Classification stages of the presented approach.

2.1 Octave Programmed Voltage Disturbances
2.1.1 *Voltage Sag*
The decremented level of voltage, between a length of 0.5 cycle to few seconds can be explained as a voltage sag. Sag are programmed by using the math model as in equation (1), Table 1. Where 'V' is amplitude value set to 1, 'ω' is angular frequency, 'γ' is constant value.

The waveform, in Figure 3, is produced for a time period of 0.4 seconds and voltage sag is generated for 0.1 to 0.3 seconds [2].

Table 1. Math models for generating the voltage disturbances

SI. No.	PQ disturbances	Math Model
1.	Voltage Sag	Sag(t) = V*(1 - γ (u(t-t1) – u(t-t2)))*sin(ωt)
2.	Voltage Swell	S(t) = V*(1 + γ (u(t-t1) – u(t-t2)))*sin(ωt)
3.	Voltage Transients	T(t) = V*(cos(ωt) + C* exp(-(t-t1)/α) * cos(ωn(t-t1))(u(t2)-u(t1))
4.	Harmonics	H(t) = V*(β*(sin(ωt) + sin(3*ωt) + sin(5*ωt)))

2.1.2 *Voltage Swell*
The incremented level of voltage value for a brief period of time, 0.5 seconds to a minute. The entire signal is generated for 0.4 seconds of duration using the math model in equation (2), Table 1. The swell wave is generated for 0.1 to 0.3 seconds, Figure 4 [2].

2.1.3 *Voltage Transients*
The unexpected burst of voltage levels in the normal voltage signal, occurring for a millisecond length. The duration is less than the length of sag and swell duration. The waveform is generated based on the equation (3), Table 1 using Octave as in Figure 4, Where 'C' is constant, α = 0.0015 [2].

2.1.4 Harmonics
The voltage harmonic signal is generated based on the equation (4), Table 1 using a Octave program. It can be defined as the voltage signals having frequencies distinct than its fundamental frequency. The waveform is generated for a duration of 0.4 seconds as in Figure 5.The value of 'β' is set to 0.005 [2].

3. MULTIVARIATE EMPIRICAL MODE DECOMPOSITION (MEMD)
The EMD and EEMD algorithms are used to identify the unstable PQ disparities, which could be used only for the univariate signals [3,4]. To analyze the three-phase signals at a time economically, MEMD is a needful task [5]. The basic Empirical Mode Decomposition directly computes the mean and envelope of the power disturbances. But, the MEMD approach computes the multiple dimensional mean and envelopes by using projections.

Let {y(t)} t = 1 to 3 be a three-phase voltage signal with $d^{\theta k}$ be a collection of direction vectors along the direction θ_k . The algorithm as follows,

Step 1: Compute the three-phase projection of the input signal y(t), $ip^{\theta x}$ along the direction $d^{\theta x}$.

Step 2: Locate the envelopes projection time instants.

Step 3: Form a envelope by using interpolation $e^{\theta x}$ (t), x=1, to D where 'D' is the direction vectors set.

Step 4: Evaluate the mean,

mean(t) = (Higher_Envelope+Lower_Envelope)/2 (1)

Step 5: Estimate the difference,

di(t) = y(t) – mean(t). (2)

Step 6: If the extreme values and and zerocrossing value diverges by value one and suppose if di(t) is a zero mean process then say it a first IMF (IMF_1).

Else, substitute y(t) by di (t) in Step (1) and repeat the process.

Step 7: Estimate the residue value,

Residue(t) = Residue(t) – IMF_1. (3)

The process is repeated until the residue value is obtained as a monotonic function. Else, this sifting process is repeated from first step to get a monotonic function [5,6,7].

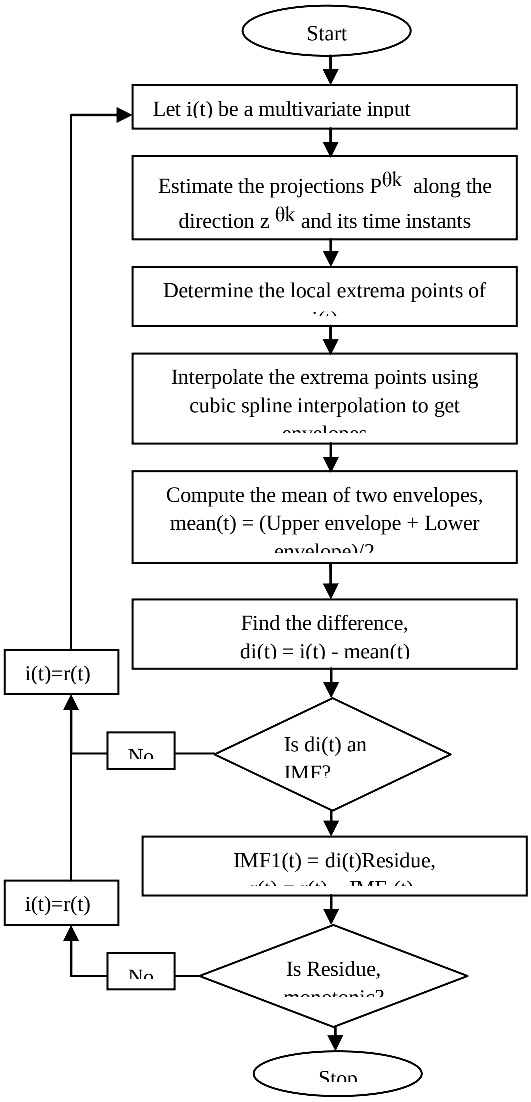


Figure 2. Flowchart of MEMD.

4. HILBERT-HUANG TRANSFORM

The Intrinsic Mode Functions (IMFs) that are acquired by the MEMD are given to Hilbert-Huang transformations to get the values of Instantaneous frequencies and Instantaneous amplitude values on which the statistical parameters are computed.

5. SUPPORT VECTOR MACHINE

Vladimir N Vapnik and Alexey Ya Chervonenkins proposed SVM. A model is constructed upon the training set to group the test data. The key part of using this is to distinguish the disparities classes. Multi-class Radial Basis Function SVM is used for the prediction is based on the LIBSVM [8].

6. EXPERIMENTS AND RESULTS

The Octave programmed voltage disparities using the math models are shown,

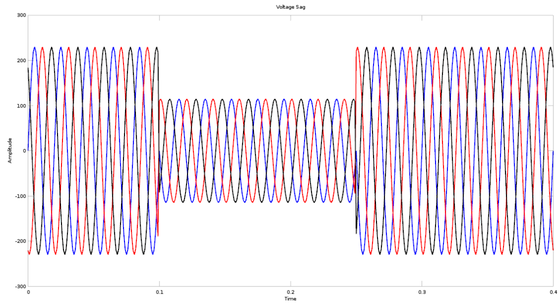


Figure 3. Octave program generated three-phase voltage sag waveform.

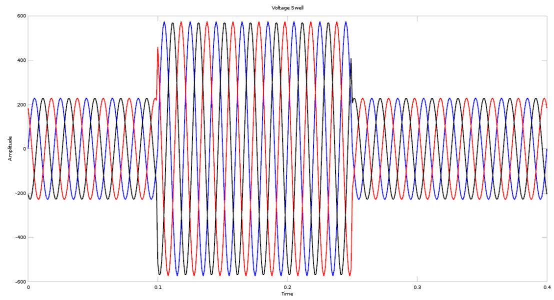
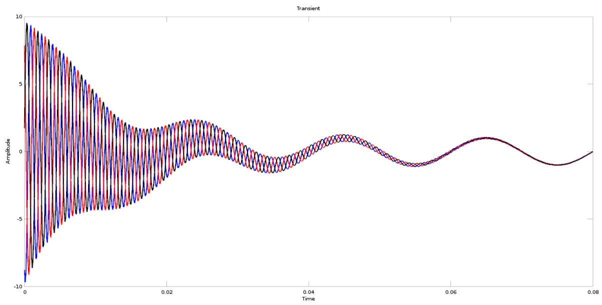


Figure 4. Octave program generated three-phase voltage



swell waveform.

Figure 5. Octave program generated three-phase transients waveform.

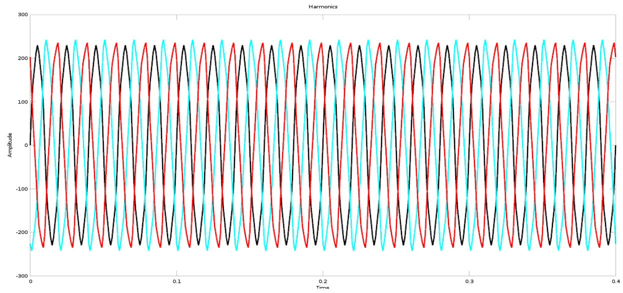


Figure 6. Octave program generated three-phase harmonics waveform.

The three-phase decomposition of voltage swell signal (IMFs) are shown in Figure 7,8,9. The eleven statistical features like first IMF value, mean, maximum and minimum values of Instantaneous Amplitude and Instantaneous Frequencies are acquired using MEMD. Some of them are given in Table 2.

Table 2. Statistical features extracted by MEMD.

	Power Quality Disturbance	Standard Deviation of IF	Mean of IF	Standard Deviation of IA	Mean of IA
1.	Voltage Swell	0.14522	0.4517	64.530	165.28
2.	Voltage Sag	0.16032	0.4966	95.459	187.61
3.	Harmonics	0.19255	0.6316	49.860	101.20
4.	Transients	0.14603	0.2525	29.810	114.30

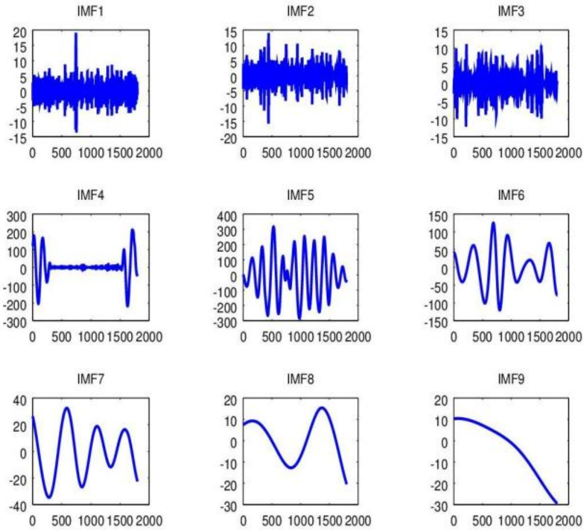


Figure 7. Intrinsic Mode Functions of the first phase swell signal.

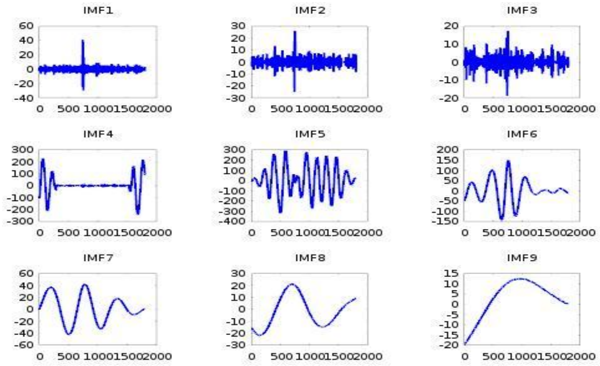


Figure 8. Intrinsic Mode Functions of the second phase swell signal.

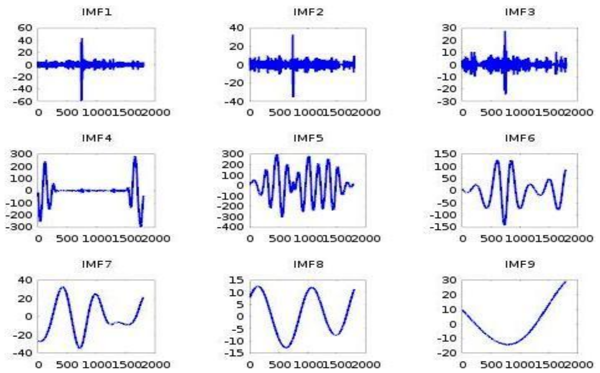


Figure 9. Intrinsic Mode Functions of the third phase swell signal.

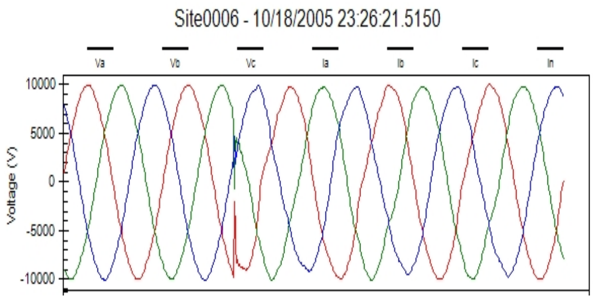


Figure 10. Online data collected from the Power System Events Library [9].

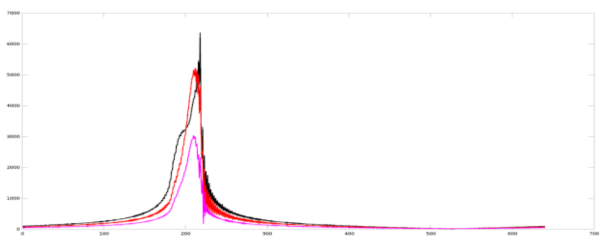


Figure 11. First Instantaneous Amplitude of all three-phase signals.

SVM classification using RBF is done and it is found that One versus Rest classification accuracy of 75.4 percentage is achieved by training the generated data and real-time online data.

7. CONCLUSION

The continuation of the Empirical Mode Decomposition for the three-phase voltage disturbances, using MEMD is analyzed and the obtained features are trained and predicted by using the Radial Basis Function kernel Support Vector Machine classifier. The fault in the three-phase voltage signal can be determined by the visual inspection of the first IA of all the three-phases. The acquired online data is also analyzed using the proposed methodologies. Therefore, locating the origin of the faults. The need of trade-off parameters and the utilization of the kernel functions are the major drawbacks of SVM. Hence, the classification utilizing Relevance Vector Machine is the expected future enhancement.

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