Pattern Recognition Methods for Detecting Voltage Sag Disturbances and Electromagnetic Interference in Smart Grids

Turgay Yalcin, Muammer Ozdemir

Abstract— **Identification of system disturbances, detection of them guarantees smart grids power quality (PQ) system reliability and provides long lasting life of the power system. The key goal of this study is to find the best accuracy of identification algorithm for non-stationary, non-linear power quality disturbances such as voltage sag, electromagnetic interference in smart grids. PQube, power quality and energy monitor, was used to acquire these distortions. Ensemble Empirical Mode Decomposition is used for electromagnetic interference reduction with first intrinsic mode function. Hilbert Huang Transform is used for generating instantaneous amplitude and instantaneous frequency feature of real time voltage sag power signal. Outputs of Hilbert Huang Transform is intrinsic mode functions (IMFs), instantaneous frequency (IF), and instantaneous amplitude (IA). Characteristic features are obtained from first IMFs, IF, and IA. The six features—, the mean, standard deviation,skewness, kurtosis of both IF and IA are then calculated. These features are normalized along with the inputs classifiers. The proposed power system monitoring system is able to detect power system voltage sag disturbances and capable of recognize electromagnetic interference component. In this study based on experimental studies, Hilbert Huang Transform based pattern recognition technique was used to investigate power signal to diagnose voltage sag and in power grid. Support Vector Machines and C4.5 Decision Tree were operated and their achievements were matched for precision and CPU timing. According to the analysis, decision tree algorithm without dimensionality reduction produces the best solution.**

Index Terms— C4.5 decision trees, electromagnetic interference, feature extraction, hilbert huang transform, power quality disturbance, smart grids, support vector machines

I. INTRODUCTION

Smart grids have been constructed structure where a number of control devices are used to provide reliability, stability and efficiency in the power generation, transmission and distribution. To enhance forecasting faults and risks in addition to ensuring protection against any possible internal and external threats, the new generation, smart grids, will be supplied with communication facilities and real time measurement techniques [1, 2]. The smart grid design is mainly based on restructuring the power industry and optimizing its resources. Smart Grids could optimize transfer capability of transmission and distribution networks to meet the demands for higher quality and more reliable power supply [1, 2]. The main benefits of the Smart Grid technologies include: minimized shutdown of the distributed generation in overload conditions, power quality improvement, improved voltage profile, coordinated restoring of the power system avoid to grid blackout [1,2,3,4].

This scientific study is supported by TUBITAK. (Project Number: 114E919)
T. Yalcin is with the Ondokuz Mayis University, Department of Electrical & Electronic Engineering, 55139, Samsun, TURKEY (e-mail: turgay.yalcin@omu.edu.tr). M. Ozdemir is with the Ondokuz Mayis University, Department of Electrical & Electronic Engineering, 55139, Samsun, TURKEY (e-mail: ozdemirm@omu.edu.tr).

A. *Voltage Sag*

Voltage sags are short-duration (less than 1 sec) reduction in voltage magnitude. This kind of disturbance is presently one of main power quality problems (Figure 1b.). Momentary increase of current has many origins in power systems such as energizing of transformers, short circuits, earth faults and starting of induction motors [5, 6].

B. *Electromagnetic Interference (EMI)*

Electromagnetic interference (EMI), side-effect results of the power conversion and control devices processes, can emerge in a wide frequency range from the basic harmonic and inter-harmonics of the mains frequency. A rise in switching frequencies gives rise to the high energy obstruction, created by the realization of the energy conversion processes, to be shifted in frequency range approximately operated (9 kHz-30 MHz) EMI range. Moreover, a new growing power quality problem especially (2 kHz-150 kHz) threatened the smart grid power quality [7]. EMI normalized voltage signal (L1-N / phase A) generated with arbitrary function generator Tektronix AFG3022C is shown in Figure 1c [2, 6].

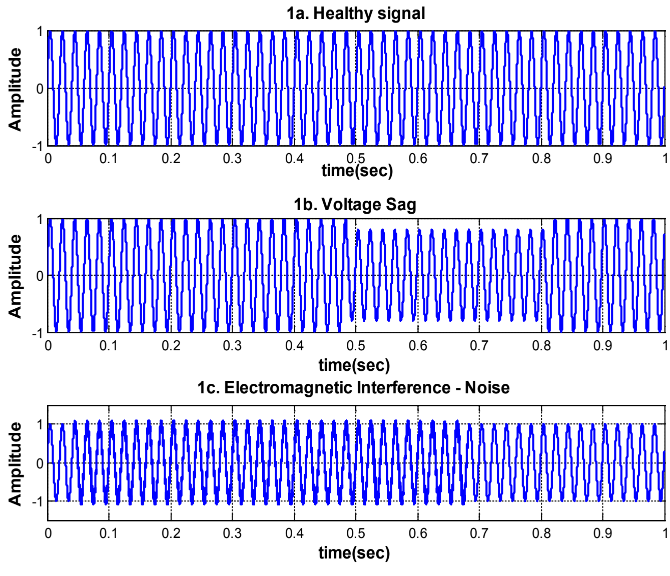

Fig. 1. Healthy signal (1a), normalized voltage sag (1b) and EMI normalized voltage signal (1c) (L1-N / phase A) generated with Tektronix AFG3022C

Hilbert Huang Transform method used for recognizing and identifying real time power quality disturbances have described in Section II.

II. FEATURE EXTRACTION

A. Emprical Mode Decomposition (EMD)

The algorithm [8, 9, 10] includes the steps:

i. Determine all the extrema of the signal, *s(t).*
ii. Find the upper and lower envelope constructed in step (i). (Interpolation of the extrema analyses with the cubic spline)
iii. Then, find the subtraction signal and the mean function of the upper and lower envelope (mean(t)), $dif(t) = s(t) - mean(t)$.
iv. Only when the iteration stops, $dif(t)$ becomes first imf $c_1(t)$; or else, branch to step (i) change $s(t)$ with $dif(t)$.
v. Find the residue signal, $res(t) = s(t) - c_1(t)$.

vi. Continue the operation from steps (i) to (vi) to attain second IMF, $c_2(t)$. Achieve $c_n(t)$, continue steps (i) – (vi) after n iterations. The routine is broken when the last imf (residual signal $res(t)$) is acquired as a monotonic function.

This routine called *sifting process. Finally,* we get residue $res(t)$, gathering of m IMF, from $c_1(t)$ to $c_n(t)$. The targeted signal can be expressed as:

$$s(t) = \sum_{i=1}^{m} c_i(t) + res(t) \quad (1)$$

we can regard $res(t)$ as $c_{m+1}(t)$ [11, 12,13].

C. Feature Generation: Hilbert-Huang Transform (HHT)

HHT [13, 14, 15] enables the real time signal $X(t)$ into the time frequency domain by merging EEMD with the Hilbert transform (Fig. 3.). *The Hilbert transform* is then implemented for each IMF component $\boldsymbol{C_j}$ generated with sifting process which is explained in Section III.A.

$$v_j(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{c_j(\tau)}{t - \tau} d\tau \quad (3)$$

$c_j(t)$ *is* real part and $v_j(t)$ is imaginary part of an analytic signal $z_j(t)$:

$$z_j(t) = c_j(t) + j v_j(t) \quad (4)$$

B. Ensemble Emprical Mode Decomposition (EEMD)

The EEMD algorithm (Fig. 2.) steps are hearunder:

i. Add noise, $wn(t)$, to target signal $s_1(t)$. $s_2(t) = s_1(t) + wn(t)$.
ii. Used EMD algorithm for decomposing the final signal $s_2(t)$.
iii. Continue steps (i) and (ii) till the trial numbers. When new imf combination $C_{ij}(t)$ is succeeded, predict the ensemble mean of the last imf. The aimed output:

$$EEMD[c_j(t)] = \sum_{i=1}^{tn} c_{ij}(t) \quad (2)$$

tn: trial numbers, *i:* iteration number and *j:* imf scale [13,14].

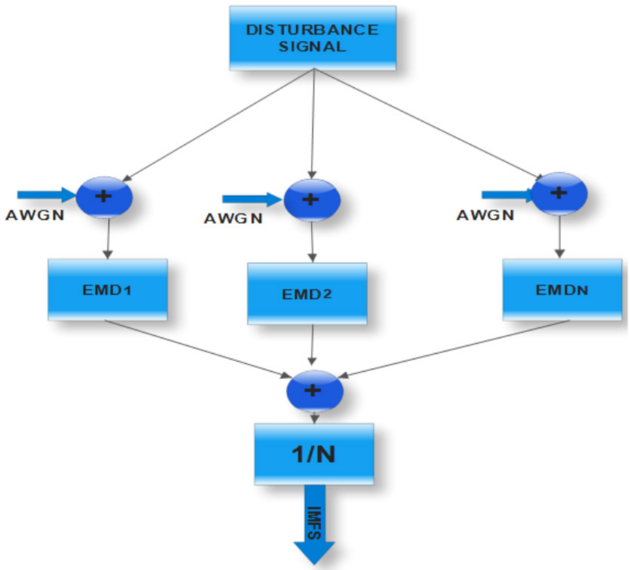

Fig. 2. The representation of the EEMD algorithm

$$z_j(t) = A_j(t) \exp(j w_j(t)) \quad (5)$$

Amplitude and *phase* expressed with equation (6) and (7):

$$A_j(t) = \sqrt{c_j(t)^2 + v_j(t)^2} \quad (6)$$

$$\theta_j(t) = \arctan\left(\frac{v_j(t)}{c_j(t)}\right) \quad (7)$$

Thus, the *instantaneous frequency* $w_j(t)$ was given by:

$$w_j(t) = \frac{d\theta_j(t)}{dt} \quad (8)$$

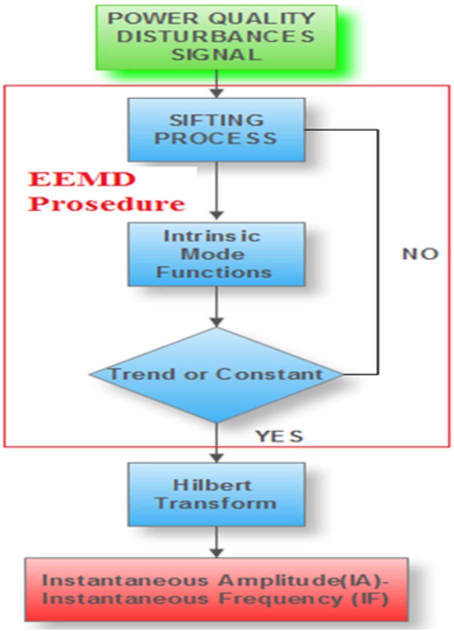

Fig. 3. Main steps of the feature generation routine with HHT

III. Experiment Set Up

In this part of the study, PQube was installed to acquire measurements, firstly in basic electricity laboratory for one phase (L1-N) records. Secondly it was utilized in computer laboratory for three phases (L1-N, L2-N, L3-N) records which its loads are computers. HHT is used in signal processing part of the study for generation of Instantaneous Amplitude (IA) and Instantaneous Frequency (IF) features. They respectively generated for real time values from PQube one phase in basic electricity laboratory, three phases in computer laboratory for computers.

A. Real Time Basic Electricity Laboratory Measurements

One phase (L1-N) voltage sag (Fig. 4.) event history which recorded by PQube is shown in Table I.

TABLE I

EVENT HISTORY (ONE PHASE)

Event_Type	Voltage Sag
Event_Magnitude	60.44%
Event_Duration_In_Seconds	0.110
Trigger_Date	2015/11/08
Trigger_Time	T 03:05:51.687
Trigger_Channel	L1-N
Trigger_Threshold	90.0% of nominal
Trigger_Sample_Number	257
Samples_Per_Cycle	128
Microseconds_Per_Sample	156.398

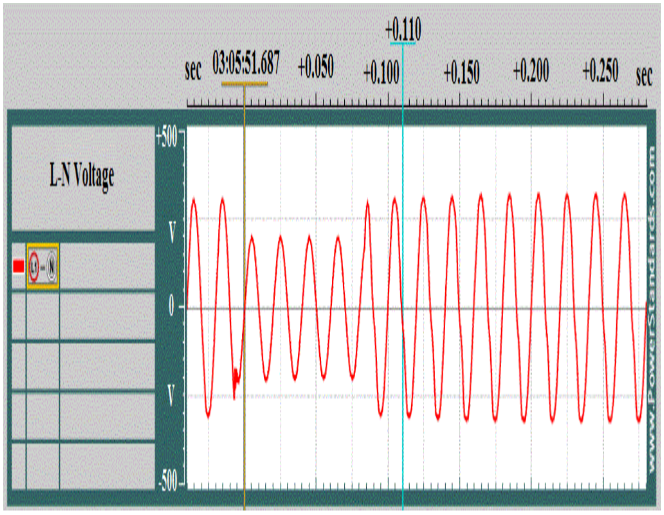

Fig. 4. Power Quality Monitor with PQube voltage sag condition of signal (2015/11/08)

Fig. 5. illustrates that first component imf1 the noise (lowest magnitude and highest frequency signal) on the line (L1-N). Lower order of imfs means high frequency and oscillation higher order otherwise.

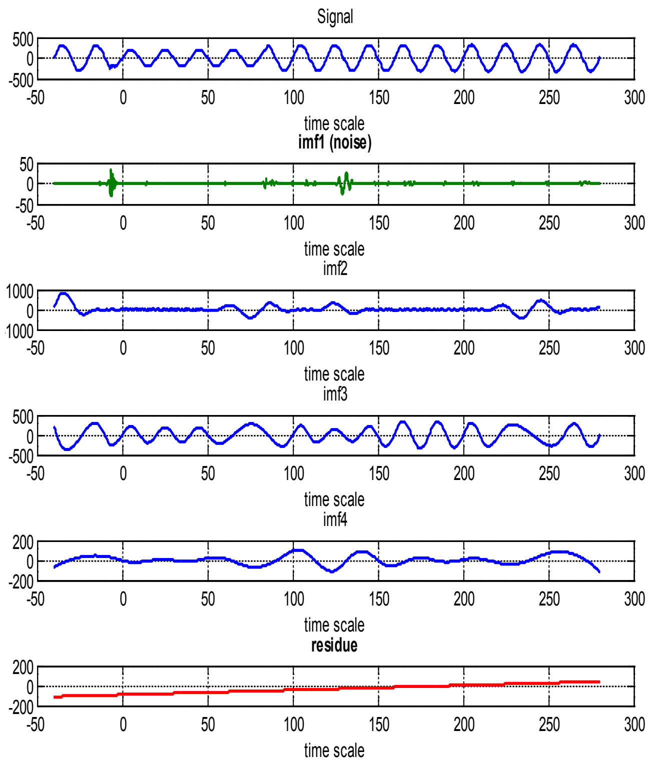

Fig. 5. IMFs for a voltage sag signal processed with EEMD

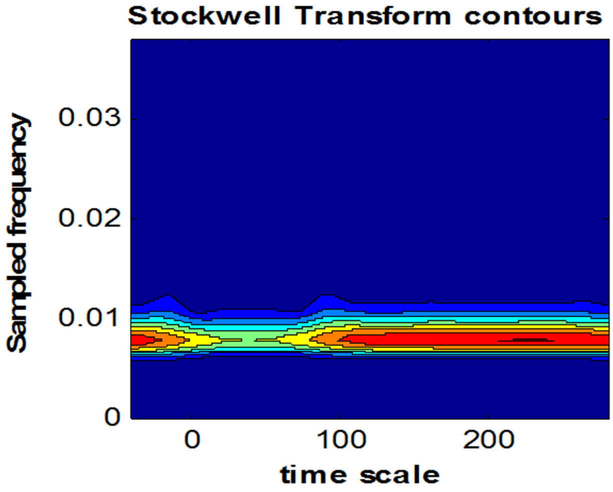

Fig. 6. Stockwell Transform (ST) contours

The Stockwell Transform (ST) is developed method related with the Gabor Transform (GT) and Wavelet Transform (WT). Several works have used ST for the analysis of PQ disturbance because it allows location in time, real and imaginary components of the spectrum [16, 17, 18, 19]. Fig. 6. shows that ST can produce proper features for detecting voltage sag. Table II shows the main advantages and disadvantages of two signal processing methods (HHT, ST).

Table II

COMPARISON OF TWO FEATURE EXTRACTION METHOD FOR PQ DISTURBANCES [25, 28]

	HHT	ST
Advantages	Appropriate for feature extraction of non-linear non-stationary signal, generates perpendicular imfs whereby instantaneous amplitude and phase can be easily assessed	Maintain time and frequency representation. Good time-frequency resolution
Disadvantages	For narrow band conditions is limited, end effects	Does not accomplish real-time requirement based on block processing, false harmonics measurement owing to dependency of frequency window width.

B. Real time Computer Laboratory measurements

For 3 phases (L1-N, L2-N, L3-N) real time processing the first intrinsic mode function is removed with the addition (superposition) of remain components to reconstruct the analyzed signal (Equ. 1.). Respectively, fig. 7. and fig. 8. show that after removing noise component normal and voltage sag cases.

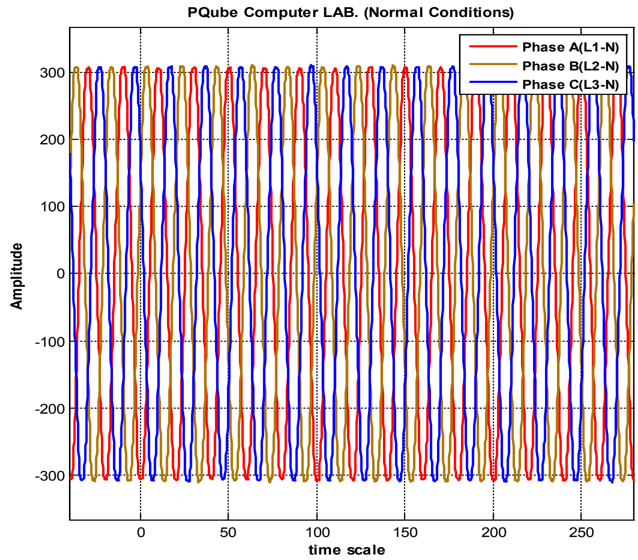

Fig. 7. After removing first imf normal condition of signal

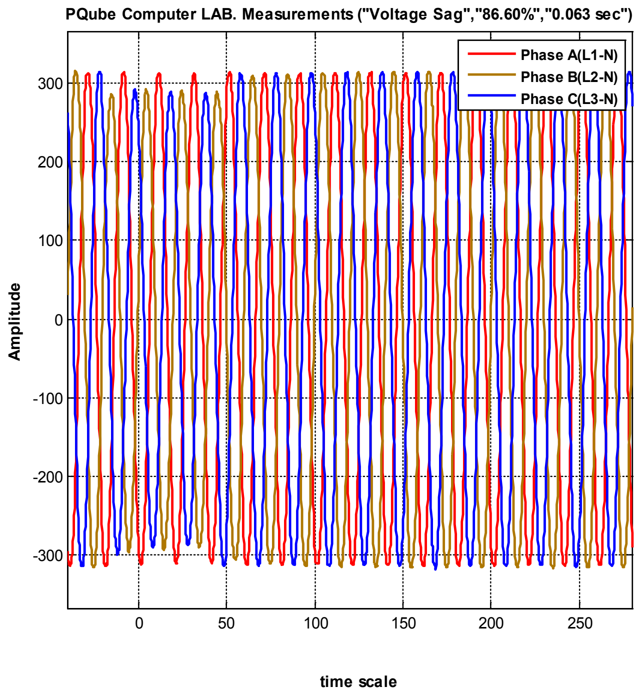

Fig. 8. After removing first imf voltage sag condition of signal

Fig 8. illustrates real time computer laboratory measures that after reconstructing the voltage sag (rate: 86.60%-duration: 0.063 sec) signal, namely the first imf removing from the noisy component. In addition, voltage sag occurred on phase B-C as a result of this case different load types and number of computers on line. This is main vision of this scientific work to identify the fault on active different load types.

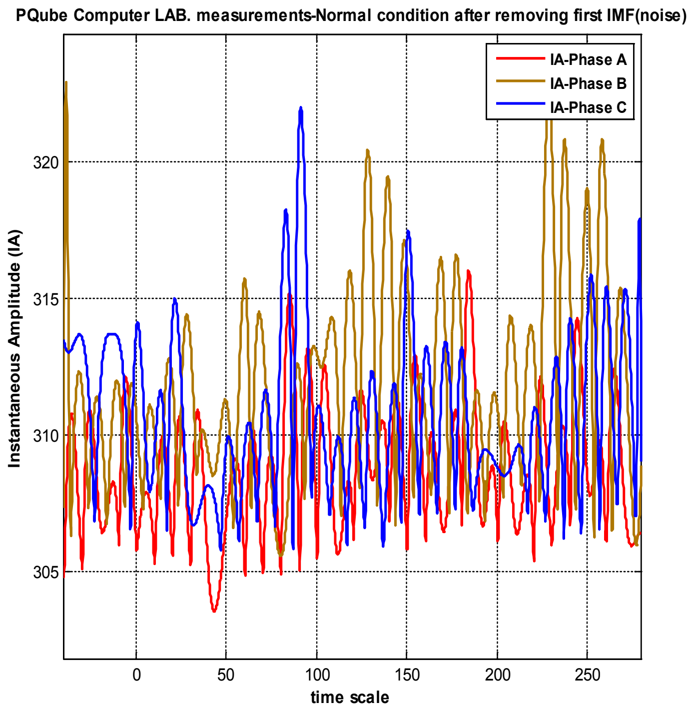

Fig. 9. IA corresponding to remove first imf normal condition of signal

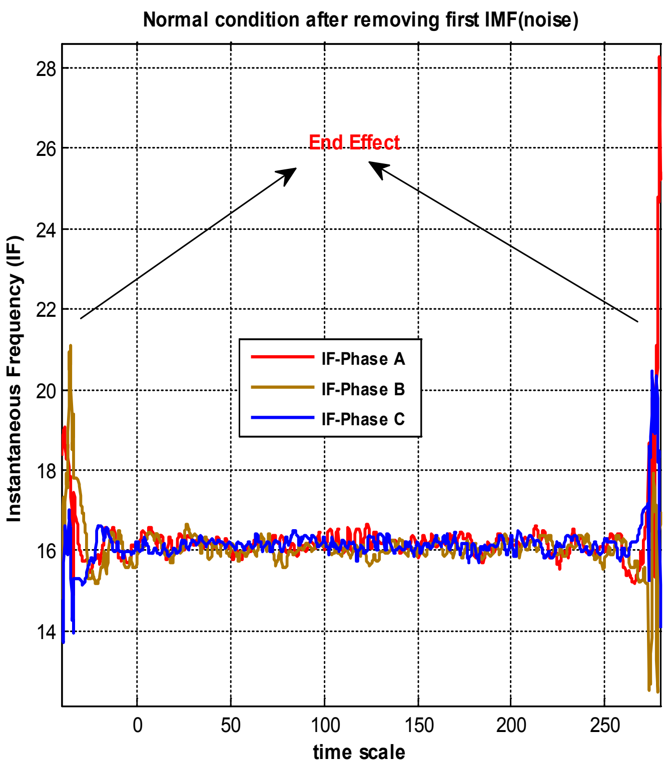

Fig. 10. IF corresponding to remove first imf normal condition of signal

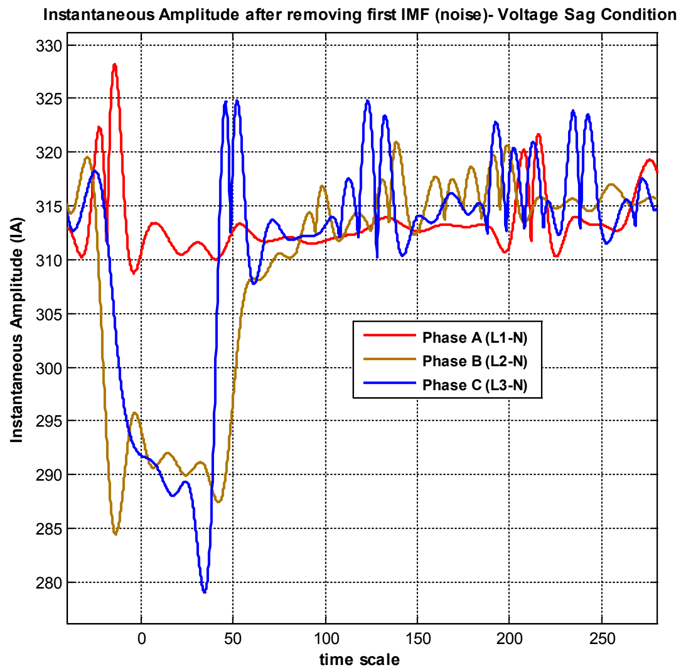

Fig. 11. IA corresponding to remove first imf voltage sag condition of signal

The results show explicitly different pattern in Fig. 9.- normal condition as for Fig. 11. – voltage sag condition. Also it is clearly shown in fig. 11. voltage sag on two phases (L2-N, L3-N). This information will be used for evaluating active loads types and risk management of the grid.

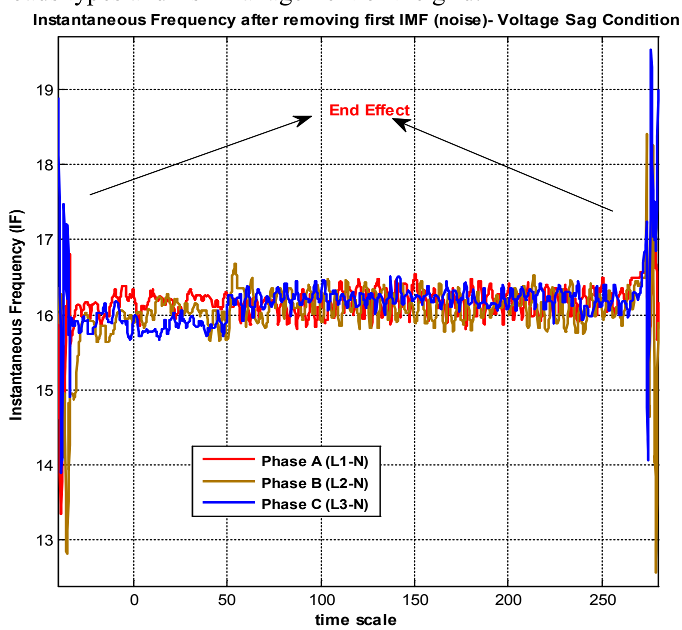

Fig. 12. IF corresponding to remove first imfs voltage sag condition of signal

IF signal can use for separation for two cases but there is end effect problem that have to be solved. This is another future work of the study. When cubic spline fitting is computationally demanding, generates distortions near the end points. This is a technical problem that causes data failures and peaks at the beginning and at the end of the signal. This fault will be investigated on HHT (Fig. 10. - 11.).

C. Feature Selection

For diagnosis of disturbances, extracted features are produced from firstly EEMD method so as to classify the voltage sags in grid. After reconstruction signal without noisy part, first imf pre-processing stage. Second stage IA and IF) are generated by means of HHT. The statistical analysis and classification for identification power quality disturbances. The following features were extracted: mean, standard deviation, skewness of IA and IF**.** Selecting appropriate features of voltage sag events are highly crucial for diagnosis of the disturbance. The primary schematic model consists of four steps as shown in Fig. 13.

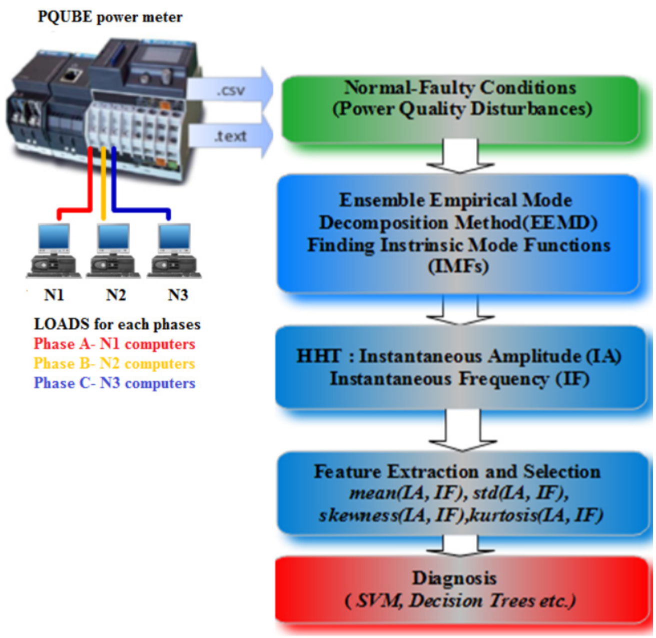

Fig. 13. Schematic model of identification of PQ disturbance

IV. PQ DISTURBANCES CLASSIFICATION TECHNIQUES

A. Support vector machine

Support Vector Machine (SVM) methods, which are developed by Vapnik, whereby statistical learning technique being the basis contributes a novel machine learning method. SVMs are linked supervised learning methods used for classification and regression [20, 21, 25, 28].

B. Decision Trees

Decision trees are methods that utilize divide-and-conquer approaches as structure learning by induction [22, 23]. The C4.5 algorithm was developed by Qinlan, contains the generation of a tree whereby a training set, finding the information gain criterion to find the finest attribute/feature to be used at each node. Furthermore, the algorithm applies the post pruning approach to diminish the size of the tree and prohibit over fitting. C4.5 is a technique for approximating discrete-valued functions that is powerful tool to noisy data and suitable for learning distinctive statements [23, 24, 25, 26, 27, 28].

V. PERFORMANCES OF CLASSIFICATION ALGORITHMS AND DISCUSSIONS

To figure out the performance of the proposed power quality classification algorithm, a total number of 30 PQube Analyzer real time disturbances data were used. The PQ signals are divided into two categories; 20 of them were used for training and 10 of them were used for testing the proposed algorithm with shuffling the data.

In the light of Table III., it is concluded that for sigmoid kernel degree 0.01 with dimensionality reduction with Singular Value Decomposition (SVD) described in [29] is better result in terms of CPU time (3.56 sec), and for polynomial kernel d=3, is also better result CPU time (3.58) in non linear classification SVM. Decision Tree algorithm has the precision of 100% and CPU time of 4.10 sec. Eventually, C4.5 Decision tree based method is the best and gives more proper outcomes than the SVM technique without SVD. (Note: the most proper and robust classifiers for each data set are showed by Red font in Table III).

TABLE III

PERFORMANCES OF DISTURBANCE DIAGNOSE ALGORITHMS

Classifier	Precision	Time (sec)
SVM-Linear	50%	2.35
SVM-poly d=2	100%	3.75
SVM-poly d=2 preprocessing SVD (r=2)	100%	3.59
SVM-poly d=3	90%	1.91
SVM-poly d=3 preprocessing SVD (r=3)	100%	3.58
SVM-poly d=3 preprocessing SVD (r=2)	60%	1.06
SVM-RBF sigma =0.01	50%	0.36
SVM-RBF sigma =0.01 preprocessing SVD (r=3)	**100%**	**3.56**
SVM-RBF sigma =1	50%	0.40
SVM-RBF sigma =1 preprocessing SVD (r=3)	50%	0.36
DecisionTree C4.5	**100%**	**4.10**
DecisionTree C4.5 preprocessing SVD (r=3)	**100%**	**4.0606**

VI. CONCLUSION

In this real time analysis, EEMD-HHT signal processing system was used for generation features of different characteristics IA and IF for normal condition and voltage sag cases. The technique reported in this study clearly accomplishes generation of features different for normal – voltage sag cases aiming that identification of smart grid faults. Simulations results have illustrated the capability and validity of the HHT. This study shows that the proposed approach can be easily used for detecting electromagnetic interference on non-stationary signals. Results of the experiments will be conduct for relation on three phases between computer numbers and voltage disturbances for future studies. In PQ Diagnosis part of the study, SVM and Decision Tree (C4.5) were operated and their results were match for precision and CPU time. In consequence of precision and timing criteria, without dimensionality reduction with SVD, SVM-RBF (sigma =0.01) algorithm presented the best solution. Results from the simulations clarify that the proposed method is effective in detecting non-stationary PQ signal. For analyzing the real time power quality disturbance signals and classifying them, Matlab ™ Toolboxes are used for simulations.

ACKNOWLEDGEMENT

This scientific study is supported by TUBITAK. (Project Number: 114E919)

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Turgay Yalçın received the B.Sc. Erciyes University (EU), Kayseri, Turkey in 2006 and M.Sc. degrees in electrical engineering from Ondokuz Mayıs University (OMU), Samsun, Turkey, in 2010 and he is currently pursuing the Ph.D. degree in electrical engineering from Ondokuz Mayıs University (OMU).

Currently, he is an research assistant with the Department of Electrical and Electronics Engineering, Ondokuz Mayıs University (OMU), Samsun, Turkey from 2007. His areas of interest are Identification of Power Quality Disturbances, Signal Processing Methods and Machine Learning Algorithms.

Muammer Özdemir received the B.Sc. and M.Sc. degrees in electrical engineering from Black Sea Technical University (KTÜ), Trabzon, Turkey, in 1988 and 1991, respectively, and the Ph.D. degree in electrical engineering from The University of Texas at Austin (UT), Austin, TX, USA, in 2002.

Currently, he is an Assistant Professor with the Department of Electrical and Electronics Engineering, Ondokuz Mayıs University (OMU), Samsun, Turkey. His areas of interest are power systems harmonics, power quality, and power system analysis.