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Multi-Class SVM for Monitoring Power Quality Disturbances using MRA

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***Abstract*— These days, using electric powered energy and digital system are elevated. For the beyond two decades, the nonlinear hundreds and semiconductor devices are extensively utilized in electric powered electricity structures which results in various energy quality disturbances along with long duration variations (Over and under voltage, surge), brief duration versions (non-permanent interruption, sag, swell), transients, notches, harmonics and voltage fluctuation/flickering. Monitoring of such energy excellent disturbances is a high-quality assignment in energy pleasant engineering. Traditionally the power nice disturbances are detected, labeled and characterized by visual examination with high-quality revel in and know-how of electricity pleasant engineering. However it has a few demanding situations like excessive intake of time and data storage. Each PQ disturbance has specific feature therefore an automatic detection and classification of PQ disturbance changed into accomplished on this paper using Wavelet rework and SVM. SDV PQ disturbances are taken as in step with IEEE standard in a continuous 30 cycle at various places which detects the PQ disturbance and classify the signal with more accuracy. The Proposed set of rules is carried out in MATLAB.**

***Index Terms*— Power Quality (PQ), Short Duration Variation(SDV) Discrete Wavelet Transform (DWT), Multi Resolution Analysis (MRA), Daubechies (Db4), Support Vector Machine (SVM).**

I. INTRODUCTION

Integrating various renewable energy sources with the power grid along with the nonlinear loads such as variable frequency drives, electric arc furnaces on one side and the customer equipment on the other side are great sensitive to power disturbance which could cause fault or variations in the voltage and current. The impact on analyzing the quality of power has taken place for the purpose of detecting the PQ disturbance accurately, estimating the economic upshot on the power system operation and to decide a cost effective PQ mitigation technique are essential. The PQ disturbance signals from power system are processed to extract the features using various digital signal processing techniques. The features obtained are used to train the classifiers in artificial neural network to classify the PQ disturbances reliably and accurately.

Many automatic PQ disturbance detection methods are proposed [1-4].Fourier transform (FT) used to analyze in frequency domain for stationary signal. Short time Fourier transforms (STFT) which gives the information in time domain and frequency domain but width of the window is limited/fixed, most of the PQ disturbance signal are non-stationary in nature and unique feature hence the FT and STFT techniques cannot track the signal dynamics.

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Wavelet transforms have good time and frequency resolution for high frequency events and low frequency events respectively hence it is popular and best suited for continuous real time signals [5-6].

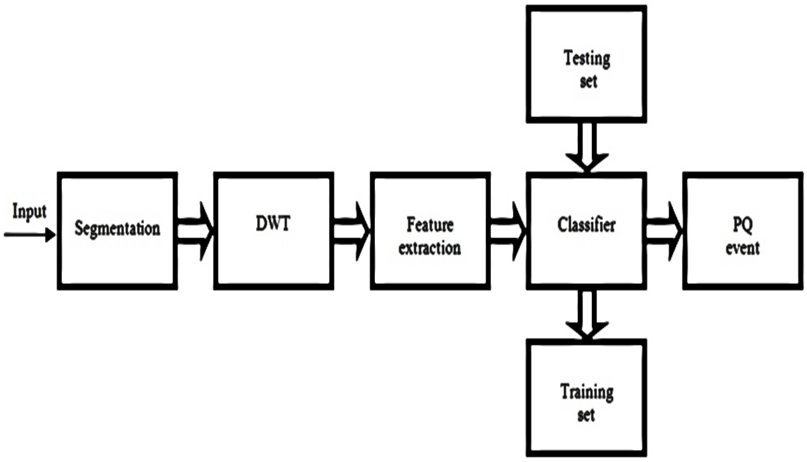

Fig.1 Block diagram

The power quality disturbances is modeled [7] using table.1 is taken as input, which was segmented as frames for analysis. Each frame consists of three cycles, which is given to DWT for detection. From the detected signal, the energy is calculated for 10 levels using Db4 wavelet.

The features are extracted, such as mean, median, crest factor, variance, Energy etc. are calculated. The extracted values are trained and tested using Multi class SVM classifier; which has very good learning ability and adaptability to the problems but lagging in explanation ability compared to fuzzy system.[8-11] here more testing parameters are enabled with less training elements, to classify the power quality event precisely.

The PQ signals which are normally accompanied with noise which reduce the signal to noise ratio hence classifying in the presence of noise is a task [12-14]

TABLE I: MODELING OF POWER QUALITY DISTURBANCE

Class	PQ disturbance	Equation of Modeling	Value of Parameters
C1	Sinusoidal wave	$x(t) = A\sin(\omega t)$	A=1.0 ; f=50Hz ; $\omega=2\pi f$
C2	Voltage Sag	$x(t) = A(1-\alpha(u(t-t1) - u(t-t2)))\sin(\omega t)$; $t1 < t2, u(t)=1, t \geq 0$	$0.1 \leq \alpha \leq 0.9$, $T \leq t2 - t1 \leq 8T$
C3	Voltage Swell	$x(t) = A(1+\alpha(u(t-t1) - u(t-t2)))\sin(\omega t)$; $t1 < t2, u(t)=1, t \geq 0$	$0.1 \leq \alpha \leq 0.8$, $T \leq t2 - t1 \leq 8T$
C4	Momentary Interruption	$x(t) = A(1+\alpha(u(t-t1) - u(t-t2)))\sin(\omega t)$; $t1 < t2, u(t)=1, t \geq 0$	$0 \leq \alpha \leq 0.09$, $T \leq t2 - t1 \leq 8T$

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II. DISCRETE WAVELET TRANSFORM AND MULTI RESOLUTION ANALYSIS

The non-stationary signals are analyzed both in time and frequency domains using Discrete Wavelet transform which gives effective and efficient results. The DWT consists of set of function namely scaling and wavelet function associated with low pass and high pass filters respectively.

The continuous Wavelet Transform of a continuous time signal x(t) is defined as

$$\boldsymbol{CWT\ \psi^{X(a,b)}} = \int_{-\infty}^{+\infty} \boldsymbol{x(t)\psi^{*}_{a,b}\,(t)dt}, \quad \mathbf{a,b \in R\ ,\ a \neq 0} \qquad \mathbf{(1)}$$

$$\text{Where } \psi^{*}_{a,b}(t) = \frac{1}{\sqrt{a}}\psi^{*}\left(\frac{t-a}{b}\right) \qquad \mathbf{(2)}$$

ψ(t) is the mother wavelet Where 'a' and 'b' are scaling and translating parameters respectively. The DWT is obtained from continuous Wavelet Transform by replacing x(t) by x(k) where x(k) is the sampled signal. The Discrete Wavelet Transform of a time signal x(k) is defined as

$$\mathrm{DWT}_{\psi}\ x(m,n) = \sum_{k} x(k)\psi^{*}_{m,n}(k) \qquad \mathbf{(3)}$$

$$\text{Where } \psi^{*}_{m,n}(k) = \frac{1}{\sqrt{a_0}}\ \psi^{*}\left(\frac{k-n\,a_0^{m}b_0}{a_0^{m}}\right) \qquad \mathbf{(4)}$$

There are different mother wavelets such as Haar, Morlet, coiflet, symlet and Daubechies wavelets. The section of mother wavelet is important because each wavelet has different properties. Daubechies wavelets (db4) are used in many applications in power system and power quality applications [8-9]. (4)

The Multi Resolution Analysis (MRA) detect and localize the non-stationary power quality disturbance signal accurately by decomposing the input signal into different resolution level corresponding to different frequency bands. MRA involves two processes such as decomposition and reconstruction.

In MRA decomposition process, the power quality disturbance signal passes through DWT which is composed of low pass and high pass filter. The low pass filter gives fine detailed version 'd1' and the high pass filter gives the coarse approximate version 'a1' of the signal whose frequency band is fs/2 at the first resolution level. The output of low pass filtered signal 'd1' is considered as an input to the second resolution level which decompose the signal into fine detailed version 'd2' and coarse approximate version 'a2' by low pass and high pass filter whose frequency band is fs/22 .

Again the output of low pass filtered signal 'd2' is considered as an input for the third resolution level which decompose the signal into fine detailed version 'd3' and coarse approximate version 'a3' by low pass and high pass filter whose frequency band is fs/23 and the process repeats for n resolution levels whose frequency band will be fs/2n.

Fig 2 shows a decomposition of four levels of a signal sampled at a frequency of 15.8 kHz into five frequency bands ‘a4’ is the level of approximation with the lowest frequency band ‘d1’,’d2’,’d3’ and’d4’ are respective detail or the high frequency band .Table 2 shows the frequency bands for the Different resolution levels of approximation and detail coefficients.

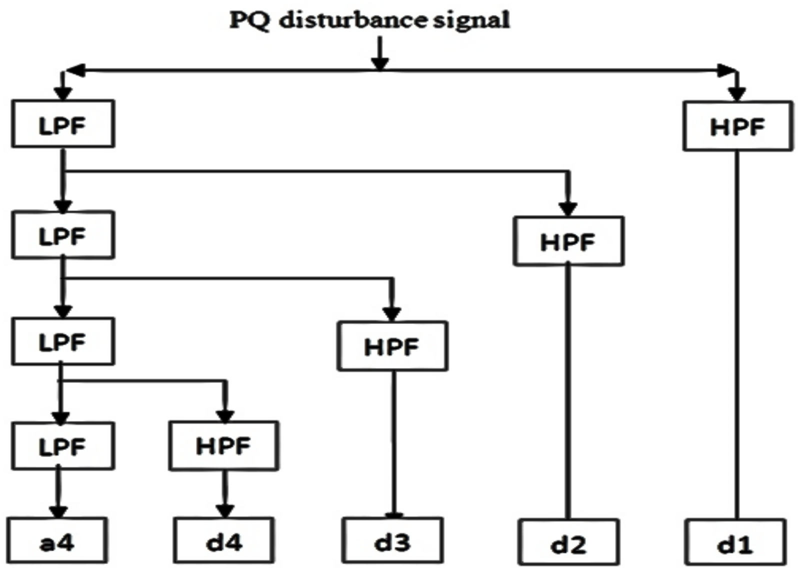

Fig. 2 MRA Decomposition

TABLE II: CORRESPONDING LEVELS OF APPROXIMATION

Levels i	**Approximation** a_i **(LPF)** kHz	**Detail** d_i**(HPF)** kHz
1	(0-7.9)	(7.9-15.8)
2	(0-3.95)	(3.95-7.9)
3	(0-1.975)	(1.975-3.95)
4	(0-0.987)	(0.987-1.975)
5	(0-0.493)	(0.493-0.987)
6	(0-0.246)	(0.246-0.493)
7	(0-0.123)	(0.123-0.246)
8	(0-0.06)	(0.06-0.123)
9	(0-0.03)	(0.03-0.06)
10	(0-0.01)	(0.01-0.03)

III. SUPPORT VECTOR MACHINE CLASSIFIER (SVM)

SVM is a powerful supervised learning method to analyze and classify huge data in PQ disturbance .The training data are taken to analyse two classes of problems initially. The decision functions of SVM classifier is given as sgn (($w^T x_i$) + w_0) by the maximum margin ,where w is the weight vector of the

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separating hyper plane in the canonical form and w0 is a term of bias. The closest distances of the point to the hyper planes of both -1 and +1 are calculated as 1/|w|. The margin separation is defined by 2/|w|.

In real time practical cases noise which corrupts data so difficult to separable by a linear hyper plane. The allowable margin of deviations, the stack variables I >0 are introduced

$$y_i\left((W^T X_i)+W_o\right)\geq 1-\xi_i\ , \quad i=1,\ldots,l \qquad \textbf{(5)}$$

The processes of training data xi, if $0 < \xi_i < 1$, the data do not have the margin maximum are still correctly classified. But $\xi i \geq 1$, the data which are misclassified by the optimal hyperplane. Thus the margin of separation are increased by leaving intra-margin points of noise occurring near the boundaries or outlier points or both, so the generalized performance is improved.

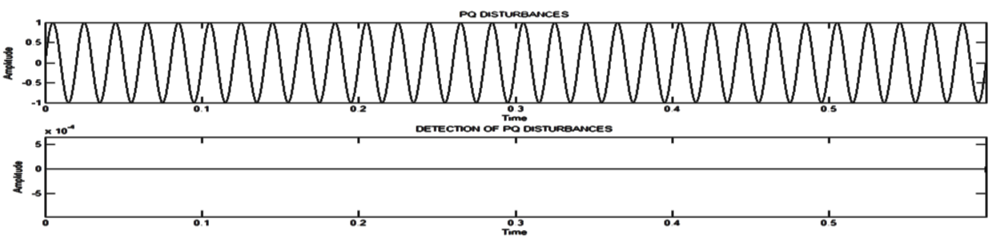
Multi-class SVM classifier are obtained by combining more than two class SVMs. The fundamental approaches are one-against-n scheme (n is the number of classes) and the one-against-one scheme. One-against-n scheme uses (n-1) two classifiers: each machine is trained for one class against all other classes. One-against-one scheme constructs a multi-class classifier i.e., (n (n-1)/2) two or more than two class machines are constructed. Each machine is trained as a classifier for one particular class against other classes. To classify test data, pair wise competitions between all the machines are performed; each winner of the machine competes against another winner until a single winner remains out. The process completes by final winner which determines the class of the test data.

IV. Simulation Results

Using MATLAB, A pure sinusoidal signal along with three PQ disturbance signals is generated for thirty cycles whose fundamental frequency of 50 Hz. The sampling frequency is 15.8 KHz and the amplitude is 1Volt per unit. Table 1 shows the modeling of various PQ disturbance signals and their control parameters. The DWT db4 family is used to decompose the signal into different levels and the detailed energy of each signal is obtained to train the SVM classifier.

Fig.3 Shows pure sine waveform which has no disturbance. The duration of disturbance detection could not be made at each resolution level of decomposition. Thus the sine wave shows the smooth line in the first level of detection. The SVM classifier classify the signal has pure sine.

Fig.4 shows the typical values of Voltage swell signal are 110-180% of the rated voltage. A 50%, 60% and 90% of voltage swell disturbance signal lasting for two cycles are simulated and shown. The duration of Voltage swell is detected clearly at the first resolution level itself and classifies accurately.



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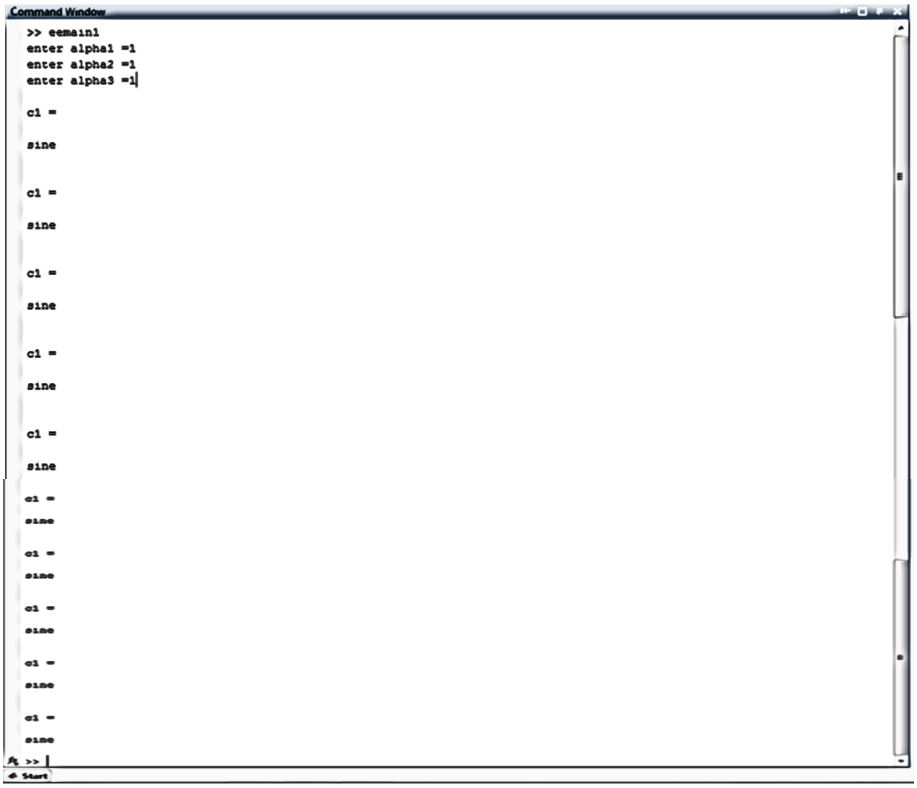
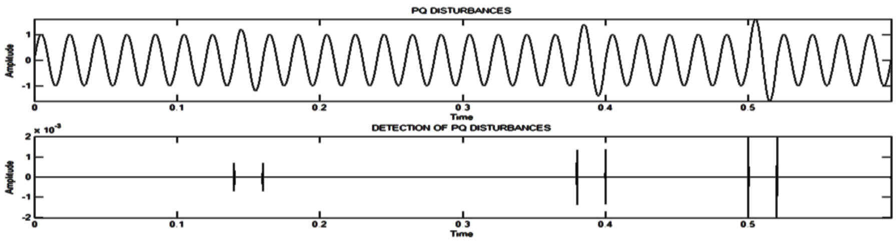


Fig.3 Pure Sine Wave, Detection and Classification



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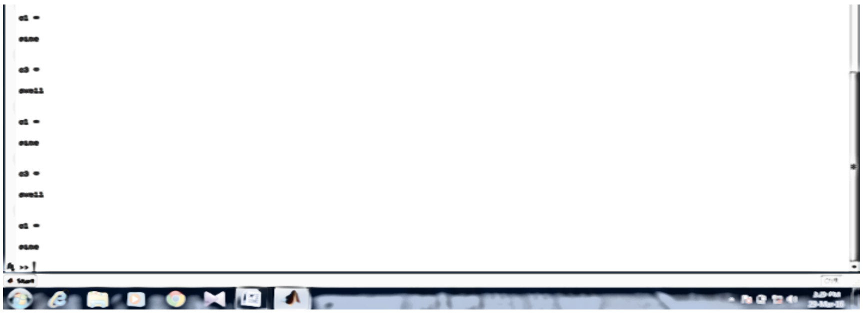

Fig.4 Voltage swell, Detection and Classification

Fig.5 Shows the Voltage sag signal whose typical values of voltage drop are 10-90% of the rated voltage lasting for half a cycle to less than 1 min. The voltage sag caused due to system faults and energization of heavy loads. A 40%, 60% and 80% of voltage sag simulated at different duration of time in a thirty cycles are shown.

Fig.6 shows Interruption of signal which describes a drop of voltage less than 1% of the rated voltage for a period of time not exceeding 1 min. The Interruption is caused by system faults and equipment failures and control malfunctions. The MRA technique detects the duration of disturbance precisely at the first resolution level and classifies the disturbance from the sine wave.

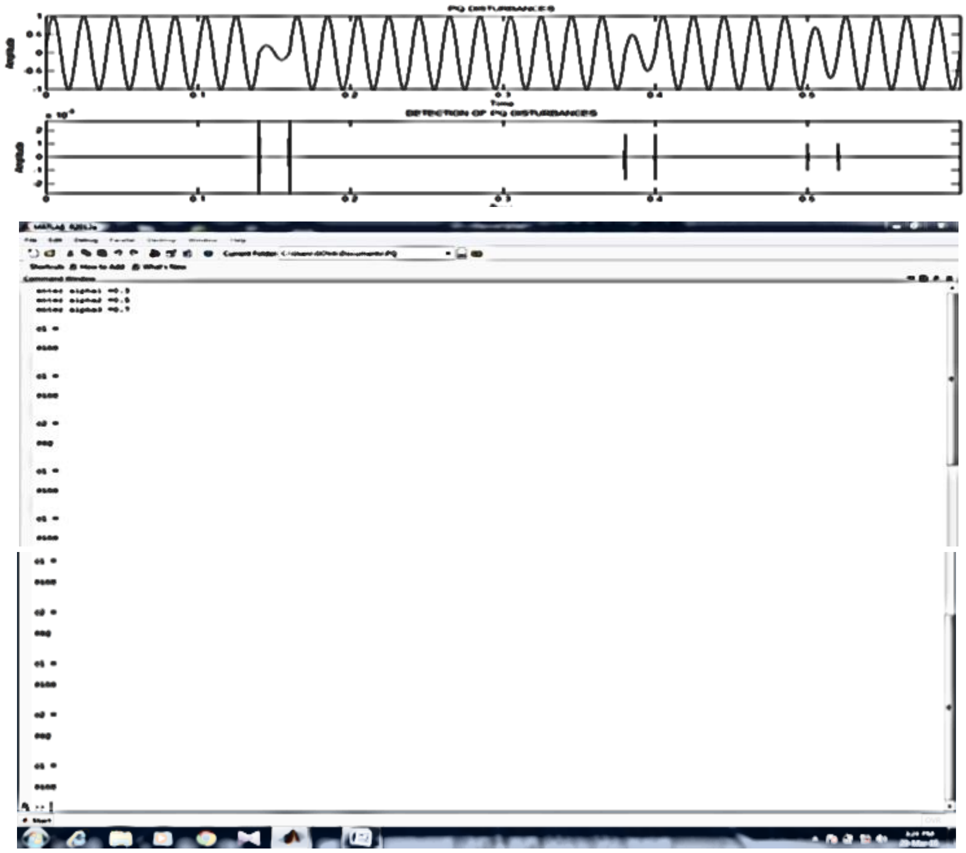

Fig.5 Voltage Sag, Detection and Classification

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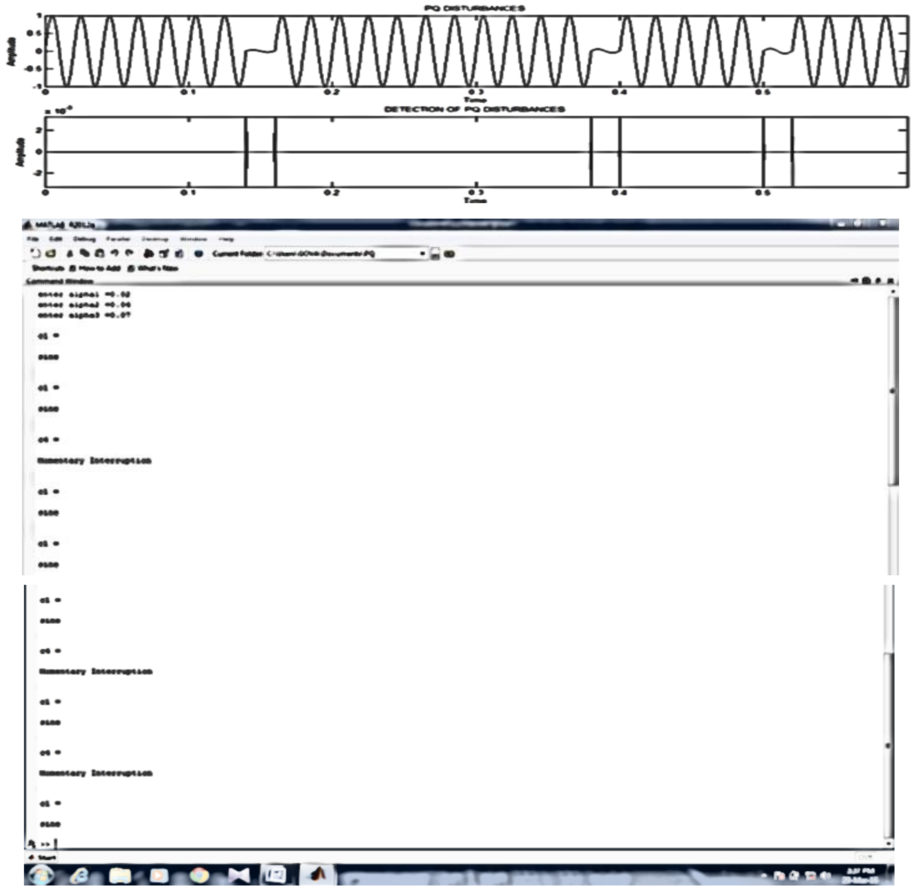

Fig.6 Momentary Interruption, Detection and Classification

Fig 7. Shows the various PQ disturbances in 30 cycles. Whose sampling frequency is 15800 Hz and amplitude is 1v with 50Hz frequency which detects the PQ distubances at the level1(d1) accurately and classifies precisely.The same algorithm can be implemented for different sampling frequencies and different PQ disturbances.

The proposed work has an advantage that, the starting time and ending time of the PQ event deteted and the features are obtained to train the multicass SVM,which classifies the PQ event .when more than one PQ event occur simultaneously in a continuous signal, the proposed scheme will classify the events with greater accuracy. The continuous Sinusoidal signal of 30 cycles is segmented to consider each cycle as a frame or three cycles as one frame. Further, each frame is applied to DWT which consist of DWT filters. Those filters segment the signal to determine detailed and approximate versions of the original signal .i.e. dn and the segmented signal from DWT which detects the pq disturbances and the energy levels of each frame (each cycle) are calculated which are called as testing data .The training data are obtained for each cycle of different values of different PQ events. If data used for training and testing are same, they are validation set. SVM classifier consists of training, validation and testing set of datas.The calculated features of testing set of data is compared with the training set of data of multiple classes to classify the disturbances of PQ event frame by frame as shown below.

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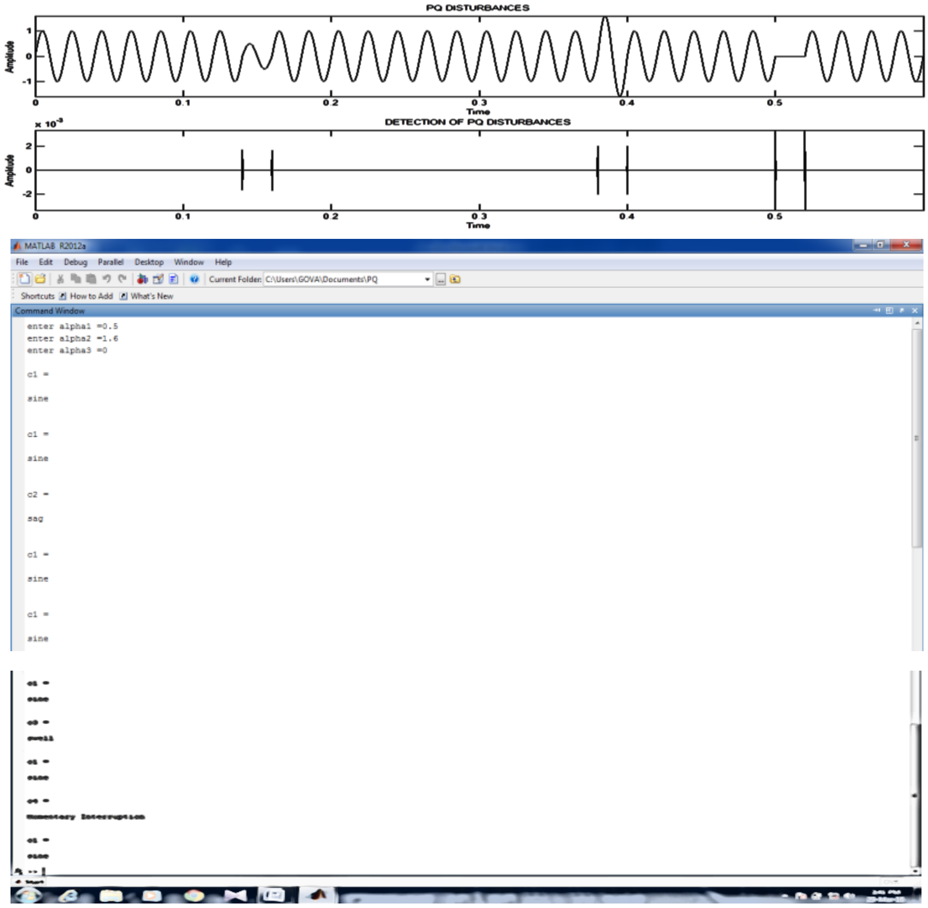

Fig 7 SDV Power quality disturbances, Detection and Classification

Fig 8. Shows the %Energy Vs Resolution levels for pure sine, 30% Voltage swell,70% Voltage sag and 50% of momentary interuption .It is observed that the pattern of votage swell is above the pure sine and voltage sag is below the pure sine . The pattern of Momentary interuption is below the pattern of voltage sag.which shows that each PQ disturbance has unique feature.

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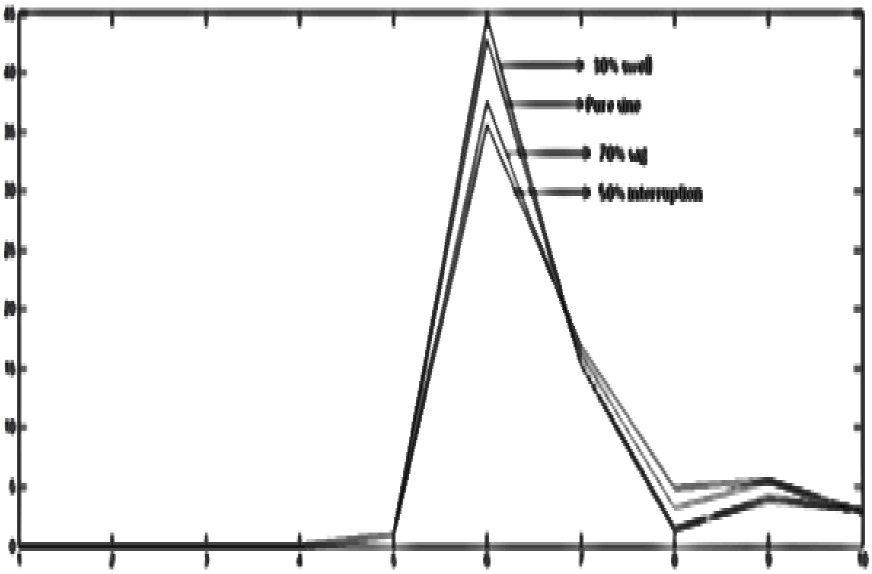

Fig 8 Shows the Energy Diagram

TABLE III: DATA OF CLASSIFICATION INCLUDING TRAINING & TESTING

PQ Class	C1	C2	C3	C4
C1	1	-	-	-
C2	-	300	-	1
C3	-	-	300	-
C4	-	-	-	299
Classification efficiency in %	100	100	100	99
Classification error in %	0	0	0	< 1
Overall Efficiency	99.66%			

$$\textbf{\% Overall Efficiency} = \frac{\textbf{Number of events correctly classified}}{\textbf{Total number of Events}}$$

V. CONCLUSION

The proposed work explains the duration of detection and classification of various Power Quality disturbances of short duration variations such as voltage sag,voltage swell and momentary interuption.The detailed energy at each resolution level are taken as a pattern to train the Multi class SVM classifier.The classifier recognizes the non-stationary Power Quality events precisely for any number of cycles and can be adapted to any sampling rate.The classifier has very good Uncertainity and Imprecision tolerance,good data mining and Maintainability,Generalisation performance are excellent. Table III shows the over all efficiency and the results are proven with the great accuracy of classification for

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multiple pq events occur simultaneously in a continous signal.The proposed technique gives an excellent result for pq disturbance even in the presence of noise.

REFERENCES

[1] A.Milchevski,D.kostadinov,D.Taskovski ,"Classifications of PQ disturbances using SVM", 2013.

[2] Anoop mathew , N.O.Gunasekar , D.Bensiker raja sigh & S.Uma meheswaran, "Detection and classification of voltage swells using wavelet transforms", 2010.

[3] N.V.H.Ravikumar , Dr.C.H.Sai babu , K.Durga shyam prasad, "Detection and improvement of PQ disturbances using wavelet transform",2012.

[4] Perumal chandrasekar , Vijayarajan kamaraj, "Detection and classification of PQ disturbances waveform using MRA based modified wavelet transform and neural network",2010.

[5] M.N.Sinha, Dr. B.R. Parekh, "Simulation of voltage sag event and it's detection method using wavelet transform",2011.

[6] L.Angrisani,p.Daponte,M.D.Apuzzo,A.Testa,"A measurement method based on the wavelet transform for PQ analysis",1998.

[7] Surya santoso,Edward J. powers, Peter hofmann, "PQ assignment via wavelet transform analysis" , 1996.

[8] Julo barros, Matiilde de apraiz, Ramon I.Diego, "A VI-based measurement instrument for detection and analysis of PQ disturbances in power system using wavelets", 2007.

[9] Weon-ki yoon and Michael J.Devaney , "Reactive power measurement using the Wavelet Transform", 1999.

[10] Subhra De.Sudipta Nath,Pampa Sinha,Sankhadip saha, "A Virtual Instrument for Real Time Power Quality Measurement under Non-sinusoidal conditions" , 2011.

[11] P. K. Dash, B. K. Panigrahi, and G. Panda "Power Quality Analysis Using S–Transform" IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 18, NO. 2, APRIL 2003.

[12] P. Pillay and A. Bhattacharjee, "Application of wavelets to model shortter power system disturbances," IEEE Trans. Power Delivery, vol. 11,pp. 2031–2037, Oct. 1996.

[13] Saxena, D, and KS Verma. "Wavelet transform based power quality events classification using artificial neural network and SVM", International Journal of Engineering Science and Technology, 2012.

[14] Mohanty, Soumya R., Prakash K. Ray, Nand Kishor, and B.K. Panigrahi. "Classification of disturbances in hybrid DG system using modular PNN and SVM", International Journal of Electrical Power & Energy Systems, 2013.

