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AUTOMATED RECOGNITION OF SINGLE & HYBRID POWER QUALITY DISTURBANCES USING WAVELET TRANSFORM BASED SUPPORT VECTOR MACHINE

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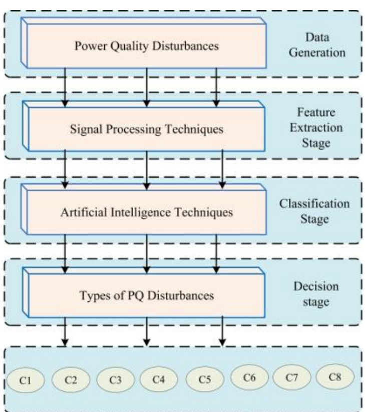
Graphical abstract



Abstract

The monitoring of power quality (PQ) disturbances in a systematic and automated way is an important issue to prevent detrimental effects on power system. The development of new methods for the automatic recognition of single and hybrid PQ disturbances is at present a major concern. This paper presents a combined approach of wavelet transform based support vector machine (WT-SVM) for the automatic classification of single and hybrid PQ disturbances. The proposed approach is applied by using synthetic models of various single and hybrid PQ signals. The suitable features of the PQ waveforms were first extracted by using discrete wavelet transform. Then SVM classifies the type of PQ disturbances based on these features. The classification performance of the proposed algorithm is also compared with wavelet based radial basis function neural network, probabilistic neural network and feed-forward neural network. The experimental results show that the recognition rate of the proposed WT-SVM based classification system is more accurate and much better than the other classifiers.

Keywords: Power quality disturbances, wavelet transform, support vector machine

Abstrak

Pemantauan gangguan kualiti kuasa (PQ) dengan cara yang sistematik dan automatik adalah isu yang penting untuk mengelakkan kesan yang menjejaskan sistem kuasa. Pembangunan kaedah baru untuk pengelasan automatik gangguan kualiti kuasa tunggal dan hybrid pada masa kini adalah menjadi kebimbangan utama. Kertas kerja ini membentangkan pendekatan gabungan jelmaan wavelet dan sokongan mesin vektor (WT-SVM) untuk pengelasan automatik gangguan kualiti kuasa tunggal dan hibrid. Pendekatan yang disyorkan menggunakan modal sintetik pelbagai isyarat kualiti kuasa tunggal dan hibrid. Ciri-ciri yang sesuai bagi bentuk gelombang kualiti kuasa pertama kali disari dengan menggunakan jelmaan wavelet diskret. Kemudiannya SVM mengelaskan jenis gangguan kualiti kuasa berdasarkan ciri-ciri ini. Prestasi pengelasan algoritma yang dicadangkan itu dibandingkan dengan wavelet berdasarkan kebarangkalian rangkaian neural dan rangkaian neural suap ke hadapan. Keputusan uji kaji menunjukkan bahawa kadar pengiktirafan pengelasan WT-SVM yang dicadangkan adalah lebih tepat dan lebih baik daripada pengkelas lain.

Kata kunci: Gangguan kualiti kuasa, jelmaan wavelet, Mesin vektor sokongan

1.0 INTRODUCTION

Power quality (PQ) is a consumer driven issue, therefore it can be defined as, "any sudden power problem manifested in voltage, current and/or frequency deviation that results in failure or mal-operation of customer equipment [1]". In the last few decades, the monitoring of electric PQ disturbances is gaining much interest. It has become a significant issue for modern power industry to protect the electrical and electronic equipment and to identify the cause of the disturbances [2, 3]. The significance of PQ is highlighted from the interest of researchers on the performance, monitoring and control of modern electrical power system [4]. The PQ is also an important issue in new, restructured and deregulated power industry. A huge economic loss due to the mal-operation of electronic equipment is one of the most important reasons for the interest in monitoring the PQ disturbances [5]. The PQ problems are created due to the growing operation of solid-state switching devices and non-linear loads, unbalanced faults, lighting control, computer and data processing equipment as well as industrial plant rectifiers and inverters [6]. Although the PQ disturbances are resulted from these devices yet these devices are mal-functioning due to the induced PQ disturbances.

The PQ disturbances, if not mitigated properly, may cause the overall interruption of the power transmission and distribution networks. Traditional PQ monitoring devices are operated manually that are utilized to measure PQ events initially, and then transfer the data to a computer for the further analysis [7]. The PQ events are identified after the data analysis in both the device and computer. However, the monitoring of PQ events in this way is a difficult task for the utilities due to the huge data to be stored. In order to overcome these drawbacks, several studies based on automatic classification of PQ disturbances have been done in recent years. For the automated recognition system artificial intelligent classifiers such as artificial neural network, fuzzy expert system and support vector machine have been proposed in conjunction with advanced signal-processing techniques such as Fourier transform, Kalman filter, wavelet transform [4]. The major steps usually involved in the automatic classification of PQ disturbances are illustrated in Figure 1.

The well-known signal-processing techniques of Discrete Fourier Transform (DFT) and Short-Time Fourier Transform (STFT) were proposed in [8, 9] for the steady-state analysis of the harmonics signals only. However, due to fixed window, the DFT and STFT are not suitable for the detection of transient PQ signals. Likewise the STFT can provide both time and frequency information but it suffers strictly from the Heisenberg uncertainty principle [10] which causes a "trade-off" between time resolution and frequency resolution. Therefore, the STFT is found inappropriate for the analysis of mostly happening non-stationary PQ disturbances. The wavelet transform with Multi-Resolution Analysis (MRA)

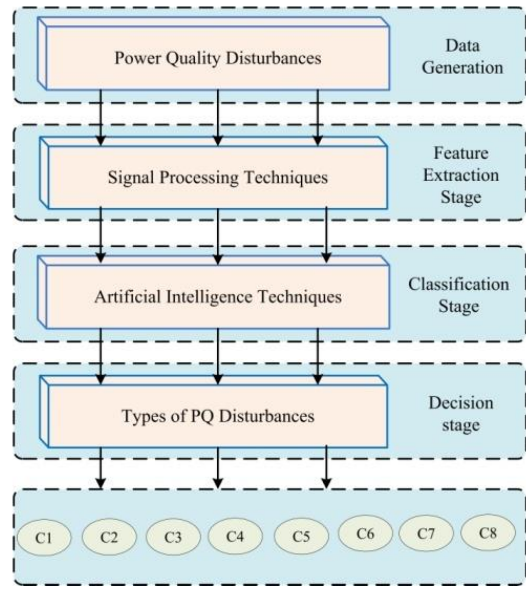


Figure 1 Block diagram of PQ disturbances classification system

provides the solution of attaining the time-frequency information and offers better time resolution for high-frequency signals, and better frequency resolution for low-frequency signals [11]. Continuous wavelet transform (CWT), discrete wavelet transform (DWT) and wavelet packet transform (WPT) have been used for feature extraction. In this paper, DWT with MRA property is proposed for the extraction of energy and entropy feature vectors that are used for training and testing the Support Vector Machine (SVM) classifier.

The features extracted from the signal processing techniques are usually combined with intelligent classifiers, such as artificial neural network [12], Fuzzy expert systems [13], support vector machine [7], extreme learning machine [14], rule-based classifier [15], hidden Markov model [16] etc. to accomplish the task of classification. The SVM classifier is proposed in this paper due to its strong classification and recognition capabilities.

The remaining parts of this paper are as follows. Theoretical background of wavelet transform and its mathematical theory and support vector machine formulation for classification are briefly described in sections 2 and 3 respectively. The proposed wavelet transform based SVM classification system is explained in section 4. The simulation results and the comparison of the proposed method to other methods are discussed in section 5. Finally, conclusions are given in section 6.

2.0 METHODOLOGY

2.1 Wavelet Transform

The wavelet transform is an advanced signal-processing tool which performs a significant role of feature extraction for the pattern recognition of PQ disturbances. It has proven a powerful feature extraction technique for PQ disturbances data using Multi-resolution Analysis (MRA) technique [32]. The signal being analyzed is decomposed into various scales of a short term waveform called the "mother wavelet". Unlike Fourier transform, the Wavelet Transform (WT) simultaneously provides time–frequency information of a signal which makes it suitable for analyzing time–frequency resolution of signals. The WT coefficients hold the characteristics of the PQ signals in the different frequency bands.

In literature, the WT has been used for feature extraction, data compression and de-noising of the PQ disturbances. The wavelet transform approaches offer continuous WT (CWT), discrete WT (DWT) and wavelet packet transform (WPT) methods for the feature extraction of signals. The CWT of a time-continuous signal x(t) is defined as [17]:

$$CWT(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\, \psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where $\psi(t)$ is "mother wavelet", a and b are the scale and translation parameters, respectively. In realistic applications, the CWT can be transferred to discrete form via a sampling way. The DWT of the discrete signal x(k) is employed to replace the CWT in Eq. (1)

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_k x(k) \psi\left(\frac{n - k b_0 a_0^m}{a_0^m}\right) \qquad (2)$$

In Eq. (2) a and b are replaced to be the functions of integers m and n respectively and a_0 and b_0 are the discrete scale and translation factor, respectively [7].

In MRA, a given signal is decomposed into different levels of resolutions, which provides a unique information on features in time-frequency domain. The waveform to be analyzed is first decomposed into two distinct representations through high pass and low pass filters, one with high frequencies (detail D_1) and other with low frequencies (approximations A_1). Mathematically, they are represented as wavelet and scale function. This process is reiterated as the waveform is filtered at subsequent levels of detail, as illustrated in Figure 2. The filtering process is accomplished by a down-sampling operator, which minimizes the information passed to preceding levels.

The energy and entropy values of the signals can be extracted from the detail and approximation coefficients $(D_1, D_2 \ldots D_l, A_l)$ of the DWT [18]. Thus the application of WT is more suitable for the feature extraction of PQ disturbances.

2.2 Support Vector Machine

Vapnik [19] introduced SVM as a supervised learning machine tool for applications of pattern recognition and classification problems. The learning of the pattern recognition approach is based on the statistical learning theory. SVM is used efficiently in large classification problems because the training of SVM can handle large feature vector dimensions more

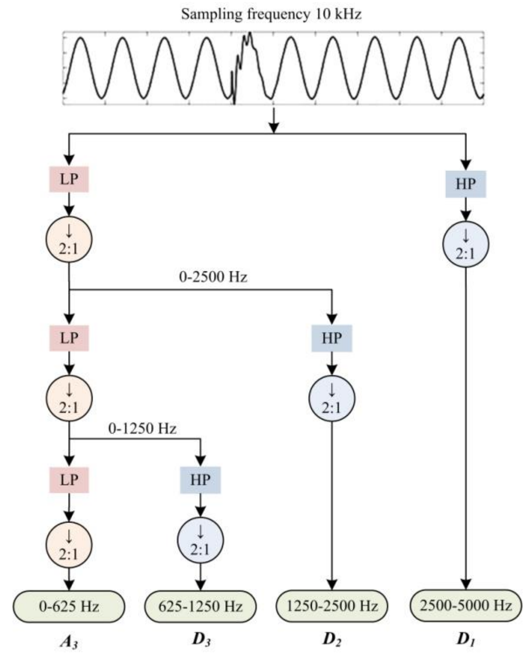


Figure 2 Consecutive decomposition of a signal by MRA technique

effectively as compared to conventional classifiers. Besides, SVM has better generalization properties than the conventional classifiers [20].

From the perspective of the principle of operation, the SVM is a linear learning machine working in the high dimensional feature space created by the nonlinear mapping of M-dimensional input vector x into a K-dimensional feature space (K>M) through the usage of function $\varphi(x)$ [11]. The separation of two classes is performed by the hyper-plane defined in Eq. (3)

$$g(x) = w^T \varphi(x) + b = 0 \qquad (3)$$

where $\varphi(x) = [\varphi_1(x), \varphi_2(x), \ldots, \varphi_k(x)]^T$ is the conversion function that is applied to convert data from input space to high-dimensional space and the parameters w, the weight vector of network $w = [w_1, w_2, \ldots, w_k]^T$ and b, the bias constitute the hyper-plane. The purpose of the learning of the SVM network in the classification problems is the maximization of the separation margin between the two classes, which are indicated here as $d_1 = 1$ and $d_2 = -1$. The hyper-plane is called the optimal splitting hyper-plane that creates the maximum distance between the plane and the adjacent data as shown in Figure 3. The optimal hyper-plane is found based on the quadratic optimization problem. Mathematically, it corresponds to the minimization of cost function $\phi(w,\xi)$ defined as

$$\min \phi(w,\xi) = \frac{1}{2} w^T w + C \sum_{i=1}^{P} \xi_i \qquad (4)$$

with constraints

$$d_i(w^T \varphi(x) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1,2, \ldots p \qquad (5)$$

In Eq.(4) and Eq. (5), C>0 is the user-specified constant indicating the regularization coefficient, $\xi_i \geq 0$ is the non-negative slack variable, and p is the number of given learning data pairs x_i, d_i.

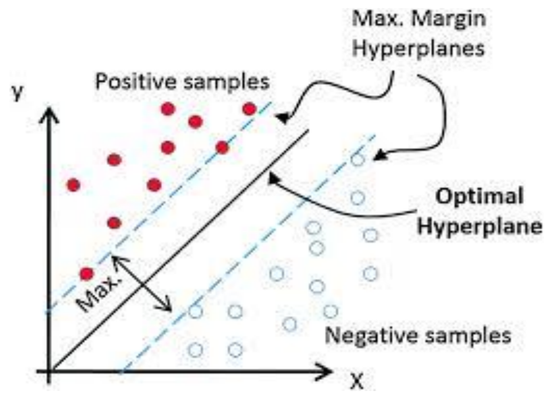


Figure 3 Optimal hyper-plane

The minimization of the second term in (4) corresponds to the maximization of the distance between the hyper-plane and the nearest points on the margins with the constraint that there are two margins on opposite sides of the hyper-plane.

2.3 Proposed Methodology

The proposed algorithm consists of three stages namely data generation, feature extraction and classification as shown in Figure 1. The data is generated using parametric equations based on the IEEE 1159 standard. A unique feature vector is created for each type of the disturbances using wavelet MRA. The PQ disturbances are classified with the help of SVM classifier by using the features obtained from the feature extraction stage. The proposed algorithm is also validated with the real-time PQ data obtained from the PSCAD/EMTDC based simulation of an 11 kV distribution system.

2.4 Data Generation

In the date generation stage, sixteen types of different PQ disturbances including one normal, 9 single and 6 hybrid PQ disturbances as shown in Table 1 were generated in Matlab 2014a environment by using parametric equations. Figure 4 depicts the ten cycles of the PQ disturbances. For each type of disturbance signal, two hundred samples (total 3200 disturbances) were generated with the randomly variation of parameters according to IEEE 1159 standard [21]. One hundred signals of each class were used as training data and the remaining one hundred signals were used as the testing data for each module of the SVM classifier.

The PQ disturbance waveforms were created at a sampling rate of 10 kHz and fundamental frequency of 50Hz. Therefore, ten cycles of each class consisting of 2000 sample points were used for classification. The advantages of using parametric equations is the flexibility of adjusting variation of parameters of each class in a wide range and in a controlled manner and the signals generated are very similar to the actual situation. Moreover, an Adaptive White Gaussian Noise (AWGN) was also uniformly added to all types of PQ disturbances with Signal-to-Noise Ratio (SNR) values of 20, 30, 40, and 50 dB.

2.5 Feature Extraction

The feature extraction is the most important stage in the automatic classification of the PQ disturbances. The signal waveforms are decomposed into wavelet coefficients using wavelet transform, then based on these features statistical features are calculated.

In the proposed method, combined energy and entropy feature vectors have been used for training the classifier. The energy features of the signals are obtained based on Parseval's theorem which states that the energy of the time domain signal x(t) is equal to the energy frequency domain (Fourier transformed) signal X[n].

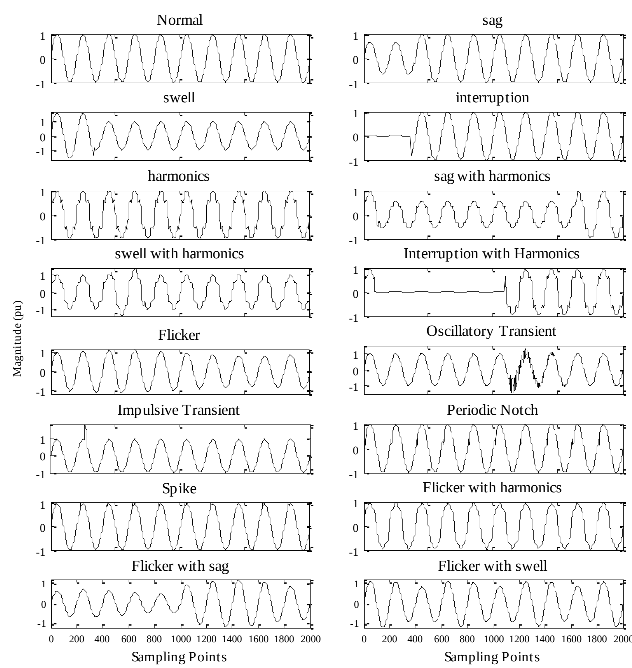


Figure 4 Power quality disturbances

$$E_{sig} = \frac{1}{T}\int_{0}^{T} |x(t)|^2 dt = \frac{1}{N}\sum_{n=0}^{N} |X[n]|^2 \qquad (6)$$

In Eq. (6), N and T are the sampling period and time period of the signal respectively. The application of Parseval's theorem to the DWT for the different frequency bands can calculate the energy of the signal as below [22]:

Table 1 Mathematical models of single and multiple Power quality disturbances

Label	PQ Disturbances	Mathematical Equations	Parameters
C1	Normal	$y(t) = Asin(\omega t)$	$w = 2\pi f$; $f = 50Hz$
C2	Sag	$y(t) = A[1 - \alpha(u(t-t_1) - u(t-t_2))]sin(\omega t)$	$0.1 \le \alpha \le 0.9$; $T \le t_2 - t_1 \le 7T$
C3	Swell	$y(t) = A[1 + \alpha(u(t-t_1) - u(t-t_2))]sin(\omega t)$	$0.1 \le \alpha \le 0.8$; $T \le t_2 - t_1 \le 7T$
C4	Interruption	$y(t) = A[1 - \alpha(u(t-t_1) - u(t-t_2))]sin(\omega t)$	$0.9 \le \alpha \le 1$; $T \le t_2 - t_1 \le 7T$
C5	Harmonics	$y(t) = A[\alpha_1 \sin(\omega t) + \alpha_3 \sin(3\omega t) + \alpha_5 \sin(5\omega t) + \alpha_7 \sin(7\omega t)]$	$0.05 \le \alpha_{3,}\alpha_{5,}\alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
C6	Sag with Harmonics	$y(t) = A[1 - \alpha(u(t-t_1) - u(t-t_2))][\alpha_1 \sin(\omega t) + \alpha_3 \sin(3\omega t) + \alpha_5 \sin(5\omega t)]$	$0.1 \le \alpha \le 0.9$; $T \le t_2 - t_1 \le 7T$ $0.05 \le \alpha_{3,}\alpha_{5,}\alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
C7	Swell with Harmonics	$y(t) = A[1 + \alpha(u(t-t_1) - u(t-t_2))][\alpha_1 \sin(\omega t) + \alpha_3 \sin(3\omega t) + \alpha_5 \sin(5\omega t)]$	$0.05 \le \alpha_{3,}\alpha_{5,}\alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
C8	Interruption with Harmonics	$y(t) = A[1 - \alpha(u(t-t_1) - u(t-t_2))][\alpha_1 \sin(\omega t) + \alpha_3 \sin(3\omega t) + \alpha_5 \sin(5\omega t)]$	$0.05 \le \alpha_{3,}\alpha_{5,}\alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
C9	Flicker	$y(t) = A[1 + \alpha_f \sin(\beta\omega t)]sin(\omega t)$	$0.1 \le \alpha_f \le 0.2$; $5 \le \beta \le 20Hz$;
C10	Oscillatory Transient	$y(t) = A[sin(\omega t) + \alpha^{-c(t-t_1)/\tau} sin\omega_n(t-t_1)(u(t_2) - u(t_1))]$	$0.1 \le \alpha \le 0.8$; $0.5T \le t_2 - t_1 \le 3T$ $8ms \le \tau \le 40ms$; $300 \le f_n \le 900Hz$
C11	Impulsive Transient	$y(t) = A[1 - \alpha\{u(t-t_1) - u(t-t_2)\}]sin(\omega t)$	$0 \le \alpha \le 0.414$; $T/20 \le t_2 - t_1 \le T/10$
C12	Periodic Notch	$y(t) = sin(\omega t) - sign(sin(\omega t)) \times \left\{\sum_{n=0}^{9} K\,[u(t-(t_1-0.02n)) - u(t-(t_2-0.02n))]\right\}$	$0 \le t_1, t_2 \le 0.5T$; $0.01T \le t_2 - t_1 \le 0.05T$; $0.1 \le K \le 0.4$;
C13	Spike	$y(t) = sin(\omega t) + sign(sin(\omega t)) \times \left\{\sum_{n=0}^{9} K \times [u(t-(t_1-0.02n)) - u(t-(t_2-0.02n))]\right\}$	$0 \le t_1, t_2 \le 0.5T$ $0.01T \le t_2 - t_1 \le 0.05T$ $0.1 \le K \le 0.4$;
C14	Flicker with harmonics	$y(t) = A(1 + \alpha_f \sin(\beta\omega t))sin(\omega t)[\alpha_1 \sin(\omega t) + \alpha_3 \sin(3\omega t) + \alpha_5 \sin(5\omega t)]$	$0.1 \le \alpha_f \le 0.2$; $5 \le \beta \le 20Hz$; $0.05 \le \alpha_{3,}\alpha_{5,}\alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
C15	Flicker with sag	$y(t) = A(1 + \alpha_f \sin(\beta\omega t))sin(\omega t)\,(1 - \alpha(u(t-t_1) - u(t-t_2)))$	$0.1 \le \alpha_f \le 0.2$; $0.1 \le \alpha \le 0.9$; $T \le t_2 - t_1 \le 7T$; $5 \le \beta \le 20Hz$;
C16	Flicker with swell	$y(t) = A[1 + \alpha_f \sin(\beta\omega t)]sin(\omega t)\,[1 + \alpha(u(t-t_1) - u(t-t_2))]$	$0.1 \le \alpha_f \le 0.2$; $0.1 \le \alpha \le 0.9$; $T \le t_2 - t_1 \le 7T$; $5 \le \beta \le 20Hz$;

$$E_{D_i} = \sum_{j=1}^{N} |D_{i,j}|^2 \qquad i = 1,2,\ldots,l \tag{7}$$

$$E_{A_l} = \sum_{j=1}^{N} |A_{l,j}|^2 \tag{8}$$

$$E_i = [E_{D_1}\, E_{D_2} \cdots E_{D_l}\, E_{A_l}] \tag{9}$$

where E_{A_j} and E_{D_j} are the energies of approximation and detail coefficients at level j.

Entropy is a measure of uncertainty used to estimate the degree of state such as irregularities, imbalance. The entropy measurement technique is considered as an ideal tool for determining the order of non-stationary waveforms. The entropy features of the detail and approximation coefficients are calculated by using Eq. (10) and Eq. (11) respectively.

$$Ent_{D_i} = -\sum_{j=1}^{N} D_{i,j}^2 \log(D_{i,j}^2) \tag{10}$$

$$Ent_{A_l} = -\sum_{j=1}^{N} A_{l,j}^2 \log(A_{l,j}^2) \tag{11}$$

Over all statistical features obtained from the MRA based DWT for any PQ signal are given by

$$Ent_i = [Ent_{D_1}\, Ent_{D_2} \cdots Ent_{D_l}\, Ent_{A_l}] \tag{12}$$

$$Feat_i = [E_i\, Ent_i] \tag{13}$$

In this stage, DWT with MRA technique at level 8 and other wavelet db4 was applied to decompose the disturbance signals into approximation and detail coefficients. All the PQ disturbances are decomposed into eight levels. The wavelet transform toolbox in MATLAB software was used to obtain the decomposition. The energy and entropy features are extracted for each detail level and last approximation level. The total size of the training and testing data set is 18 x 1600, where 18 is the size of feature of each class and 1600 is the 100 cases per class for 16 classes.

2.6 Classification

In the classification stage, the various types of PQ disturbances are classified using the SVM classifier. SVM machine learning tool is mostly used in different classification systems due to the fact that they provide a global solution, have a high speed of generalization and training. In this paper, a Lib-SVM built-in library of SVM in MATLAB environment is used. It consists of the most recent optimization method known as sequential minimal optimization (SMO) for the solution of the multi-class SVM problem. The Lib-SVM employs one versus one (OVO) method due to faster in training than the one versus all (OVA) method. The RBF kernel has been used in the SVM classifier.

Initially, the identification of the SVM parameters (optimal kernel and regularization parameters C and γ) from a wide interval is one of the most important stages in obtaining an SVM classifier. The investigation of the selected range of parameters provides the parameters resulting in the minimum classification error. Hence, an efficient search strategy is required. In this paper, a k-fold cross-validation process is applied to choose the optimal parameters. In k-fold cross-validation, the training data is randomly separated into k roughly equal subsets. The SVM prediction model is trained using k-1 subsets and validated on the subset left out. This process in continued until k times with each of the subset used as the validation subset in turn. The average of validation errors over the k trials provides a prediction of the generalization error. Hence, optimum intervals of parameters which perform the minimum root mean square error (RMSE) values are obtained. Then a tuning search process is used to the training data in the region of optimum intervals. The lowest RMSE value produced from a tuning search process shows the optimal SVM parameters.

In the next stage, the training of the SVM classifier is accomplished according to these parameters. Finally, the feature vector obtained from the feature extraction stage is employed to the SVM input.

3.0 RESULTS AND DISCUSSION

As discussed earlier, for each type of the PQ disturbances two hundred waveforms with varying parameters and time durations were generated for training and testing. The PQ waveforms were randomly separated into two parts for training and testing the SVM classifier. The LibSVM tool for SVM classifier was used to evaluate the classification performance of the extracted features of PQ disturbance waveforms. The SVM parameter setting was carried out with an RBF kernel which can behave like a linear or a sigmoid kernel.

The classification results for the sixteen types of PQ disturbances in terms of confusion matrix is shown in Table 2. The diagonal elements in the table indicate the correct classified signals, whereas off-diagonal elements show the signals which are misclassified. Table 2 shows that the proposed algorithm can effectively classify the various type of single and multiple PQ disturbances.

The performance results of the proposed algorithm are compared with the results obtained by radial basis function (RBF) neural network, multi-layer perceptron (MLP) neural network and probabilistic neural network (PNN) as shown in Table 3. The overall classification accuracies obtained by PNN, MLPNN, RBFNN and SVM are 97.19, 95.25, 96.625 and 99.06 respectively. Therefore, SVM provides the best classification results for this case.

3.1 Performance Under Noisy Environment

In electrical power distribution system, the actual PQ data consists of noise. Hence, performance of the proposed algorithm is also evaluated in the presence of noise. In actual practice the noise is randomly distributed on the sinusoidal waveform.

Table 2 Confusion matrix for classification of PQ disturbance waveforms

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	Accuracy (%)
C1	**100**																**100**
C2		**99**		1													**99**
C3			**99**						1								**99**
C4				**100**													**100**
C5					**99**					1							**99**
C6		1				**99**											**99**
C7							**100**										**100**
C8		1			1	1		**97**									**97**
C9									**99**				1				**99**
C10	1				1					**98**							**98**
C11							1				**99**						**99**
C12												**100**					**100**
C13	1								1				**98**				**98**
C14														**100**			**100**
C15								2							**98**		**98**
C16																**100**	**100**
Overall Accuracy												99.06%					

Table 3 Results comparison of RBFNN, MLPNN, PNN and SVM classifiers

Types of disturbances	Classification Accuracy (%)			
	PNN	MLP	RBF	SVM
Normal	99	97	98	100
Sag	98	96	98	99
swell	99	97	99	99
Interruption	97	95	96	100
Harmonics	99	97	97	99
Sag with Harmonics	96	94	94	99
Swell with Harmonics	96	94	96	100
Interruption with Harmonics	95	95	95	97
Flicker	97	93	95	99
Oscillatory Transient	98	92	96	98
Impulsive Transient	96	94	97	99
Periodic Notch	95	94	95	100
Spike	96	98	98	98
Flicker with harmonics	98	95	98	100
Flicker with sag	97	96	97	98
Flicker with swell	99	97	97	100
Average	**97.19**	**95.25**	**96.625**	**99.06**

Table 4 Classification results for noisy PQ disturbance waveforms

Types of PQ Disturbances	Classification Accuracy (%)				
	20bB	30dB	40dB	50dB	Noise-less
C1	99	100	100	100	100
C2	89	92	94	95	99
C3	90	94	95	94	99
C4	84	89	93	94	100
C5	88	95	95	95	99
C6	83	91	94	95	99
C7	84	90	93	94	100
C8	85	92	92	92	97
C9	82	88	92	94	99
C10	80	86	90	91	98
C11	81	87	89	92	99
C12	88	93	93	93	100
C13	98	100	100	100	98
C14	84	89	93	94	100
C15	88	95	95	95	98
C16	83	91	94	95	100
Overall Performance	**86.625**	**92**	**93.88**	**94.56**	**99.0625**

A white Gaussian noise is widely used in the studies of PQ analysis. In the proposed study, different levels of noise with the signal to noise ratio (SNR) values of 20, 30, 40 and 50 dB were applied for testing the performance. The classification results for the PQ disturbances contaminated with noise are indicated in Table 4.

3.2 Test Results On Distribution Network

A typical 132/11kV radial distribution network system in Malaysia shown in Figure 5 was simulated using PSCAD/EMTDC power system simulation software. The distribution network consists of a 132kV, 50 Hz power supply, two 132/11kV step-down power transformers and two 11kV feeders. The network contains 38 nodes that represent 34 sections each having lumped loads.
The PQ disturbances have been classified into three categories, namely (i) disturbances due to faults such as sag, swell and interruption, (ii) disturbances due to switching of capacitor banks like oscillatory and impulsive transients and (iii) disturbances due to power electronics based converters such as harmonics, notches and flickers. The multiple PQ disturbances have been created by applying any two or three types of events simultaneously.

Figure 6 shows the waveform measured at node 24 in distribution network which is generated by a single-line-to-ground fault occurred at node 24. The fault has been created at 0.08 s and cleared at 0.14 s. The sag and interruption disturbances are usually created in the fault line depending upon the magnitude of fault

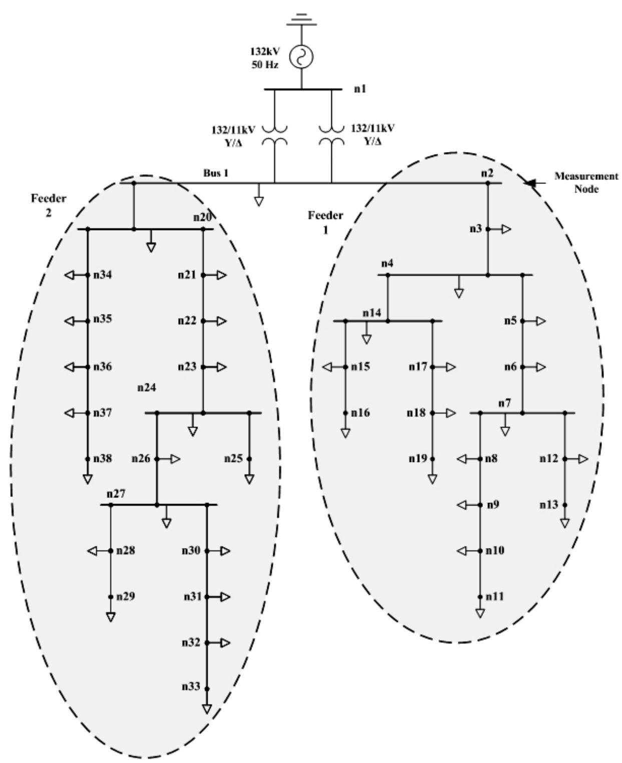


Figure 5 11kV Distribution system

resistance and swell is produced in non-fault phase. The magnitude of sag, swell and interruption depend upon the fault resistance. The impulsive and oscillatory transients were produced due to the capacitor banks

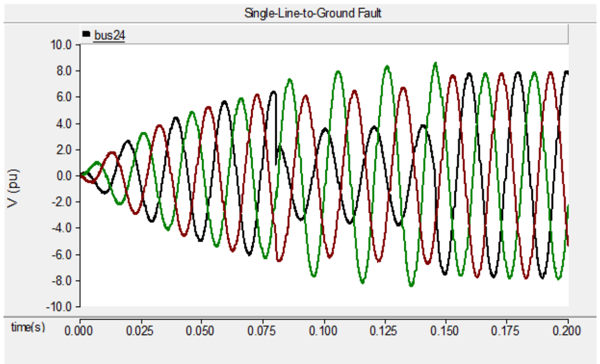


Figure 6 Single-line-to-ground fault in distribution network

and harmonics were produced due to the application of six pulse bridge rectifier. The hybrid PQ disturbances were generated by applying the disturbances creating loads simultaneously. The classification accuracy results obtained for the distribution network are shown in Table 5.

Table 5 Classification results for distribution network PQ data

Types of disturbances	Classification Accuracy (%)		
	Training /Testing Patterns	Correctly Classified	Misclassified
Normal	100	97	3
Sag	100	96	4
swell	100	97	3
Interruption	100	95	5
Harmonics	100	97	3
Sag with Harmonics	100	94	6
Swell with Harmonics	100	94	6
Interruption with Harmonics	100	95	5
Flicker	100	93	7
Oscillatory Transient	100	92	8
Impulsive Transient	100	94	6
Periodic Notch	100	94	6
Spike	100	98	2
Flicker with harmonics	100	95	5
Flicker with sag	100	96	4
Flicker with swell	100	97	3
Average	**100**	**95.25**	**4.75**

3.3 Comparative Analysis

The classification performance results of the proposed WT-SVM classification system have been compared with those recently reported similar methods in literature. The comparative results are presented in Table 6. The comparison of results shows that the proposed algorithm is capable of classifying the 16 types of single stage and multiple PQ disturbances with the highest classification accuracy of 99.06%. Therefore, this method is suitable for practical implementation for automatic classification of PQ disturbances.

Table 6 Comparison of classification accuracy with proposed methods in literature

S. No.	References	No. of PQ Disturbances	Classification Accuracies
1	Hu, *et al.* [23]	6	98.4
2	Moravej, *et al.* [24]	9	98.89
3	Eristi and Demir [7]	5	98.51
4	Zhang, *et al.* [25]	7	97.7
5	Foroughi, *et al.* [26]	4	99.5
6	**Proposed method**	**16**	**99.06**

4.0 CONCLUSION

In this paper, an intelligent pattern classification system using WT-SVM has been proposed for the automatic classification of single and multiple PQ disturbances. A suitable energy-entropy feature vector is acquired from the wavelet MRA for training and testing the SVM classifier. The performance of the SVM classifier is also compared with the PNN, RBF and MLP neural network classifiers. This illustrates that the performance of the suggested algorithm is quite superior than the other similar classification systems proposed in literature. The SVM classifier has a significant performance and less computation time. The SVM is observed to be much faster, especially in terms of calculation time and have a higher pattern classification performance than the neural network classifiers. The effectiveness of the proposed WT-SVM algorithm was checked with the PQ disturbances obtained from the parametric equations as well as from a real time 11kV distribution model. The proposed WT-SVM algorithm is found a powerful tool so that it can be applied in any real-time applications.

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