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Complex Neural Classifiers for Power Quality Data Mining

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Abstract – This work investigates the performance of fully complex- valued radial basis function network(FC-RBF) and complex extreme learning machine (CELM) based neural approaches for classification of power quality disturbances. This work engages the use of S-Transform to extract the features relating to single and combined power quality disturbances. The performance of the classifiers are compared with their real valued counterparts namely extreme learning machine(ELM) and support vector machine(SVM) in terms of convergence and classification ability. The results signify the suitability of complex valued classifiers for power quality disturbance classification.

Keywords: Power quality, Fully complex valued radial basis function network, Complex extreme learning machine, Support vector machine, S-Transform

1. Introduction

In recent years the use of sensitive loads by the customers is on the rise. As these loads are susceptible to disturbances there is a demand for clean power [1]. Poor power quality caused by these disturbances result in mal function of the loads. To provide clean power and improve the power quality the causes of these disturbances must be known to initiate corrective action [2]. To achieve this it is necessary to develop efficient methods to detect and classify the power quality disturbances. Towards this it is desirable to develop data mining methods for detecting, classifying and analysing the disturbances [3-6]. This involves the application of signal processing tools for feature extraction and statistical or artificial Intelligence classifiers for classifying the disturbances. The researchers have applied signal processing tools like fast fourier transform [7], wavelet transform [8], wavelet packet transform, S-Transform [9-11] for extracting the features required for analyzing the power quality disturbances. The wavelet transform is a promising tool for detecting and extracting the features for time series data. However S-Transform has gained popularity due to its superior pattern recognition characteristics in the presence of noise [11,12]. Hence this work engages the use of S-Transform for extracting the features. The features extracted using S-Transform contain information with respect to power quality events. The features thus obtained need to be combined with variety of pattern classifiers such as support vector machine, extreme learning machine, probabilistic neural network, fuzzy Logic for power quality event classification [13-15]. The above mentioned classifiers are real valued classifiers.

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In recent years the researchers have analysed the application of complex variants of neural network for solving regression and classification problems. The basic structure and learning algorithms of complex valued radial basis function network were first discussed by chen et al. The authors have solved Ex-OR problem using complex neural approach [22]. Complex classifiers have been applied for real valued classification as well and results signify complex classifiers outperform the real valued counter parts. Another factor that has generated consider-able interest in complex valued classifiers is the applications like telecommunication, medical imaging signals involve complex valued signals [19-22]. In [16] the authors have proposed fully complex valued activation function for complex-valued RBF network. This is referred as FC-RBF. The FC-RBF algorithm outperforms other complex valued RBF networks. A fully complex extreme learning machine (CELM) has been proposed by Li et al [23]. T he authors have presented weighted circular complex valued extreme learning machine for imbalanced learning and the results indicate the proposed technique outperforms conventional complex ELM [25]. In [26] a fully complex valued network has been proposed for human action recognition and the results fortify the superiority of the algorithm. Hung et al have proposed incremental extreme learning machine with fully complex valued hidden nodes [24].

The analysis of literatures reveal that complex classifiers have advantage over real valued classifiers. In this prelude this work engages the use of complex valued radial basis function network and complex extreme learning machine (CELM) for classification of single and combined power quality disturbances and their performance is compared with real valued algorithms namely SVM and ELM.

2. Feature Extraction Using S-Transform

In order to recognize the power quality events it is necessary to first distinguish the signals and then classify them[10]. To distinguish various events it is necessary to extract significant facts about the signals. This is done by time frequency transformation techniques. One of the widely used time frequency transformation techniques is the S-Transform [12]. The advantage of S-Transform is that it preserves the phase information of the signal while providing variable resolution. In comparison with other transformation techniques S-Transform is less susceptible to noise. This technique combines the short term fourier transform and the wavelet transform. The derivation of ST is done from wavelet transform by modifying the phase of the window function or mother wavelet. For a signal, x(t), the S-Transform is derived [12] as the product of the signal and a phase correction function $e^{-i2\Pi ft}$

The S-Transform of x(t) is defined as

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) g_f(\tau - t) \;\; \mathrm{e}^{\text{-i2}\Pi\text{ft}} dt \tag{1}$$

where $g_f(\tau)$ is the gaussian modulation function defined as

$$g_f(\tau) = \frac{|f|}{\sqrt{2\pi}} e^{-\left(\frac{\tau^2}{2\sigma^2}\right)} \tag{2}$$

and

$$\sigma = \frac{1}{|f|} \tag{3}$$

The expression becomes

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-\left(((\tau-t)^2 f^2 \big/ 2\right)} e^{-i2\Pi ft} dt \tag{4}$$

The discrete version is calculated from the fast fourier transform. The discrete Fourier Transform of the time series x(t) is obtained as

$$H\left[\frac{n}{NT}\right] = \sum_{k=0}^{N-1} x(kT) e^{-(2\pi i/N)nk} \tag{5}$$

The discrete S-Transform is obtained by allowing $f \longrightarrow n\big/NT$ and $\tau \longrightarrow jT$

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left(\frac{m+n}{NT}\right) G(m,n) e^{i2m\pi j/N} \tag{6}$$

where $G(m,n) = e^{-2\pi^2 m^2/n2}$ and j, m, n=0,1,..., N-1.

The discrete inverse of the S-Transform can be obtained as

$$x(kT) = \sum_{n=0}^{N-1} \left[\sum_{j=0}^{N-1} S\left(jT, \frac{n}{NT}\right) \right] e^{i2nk} \tag{7}$$

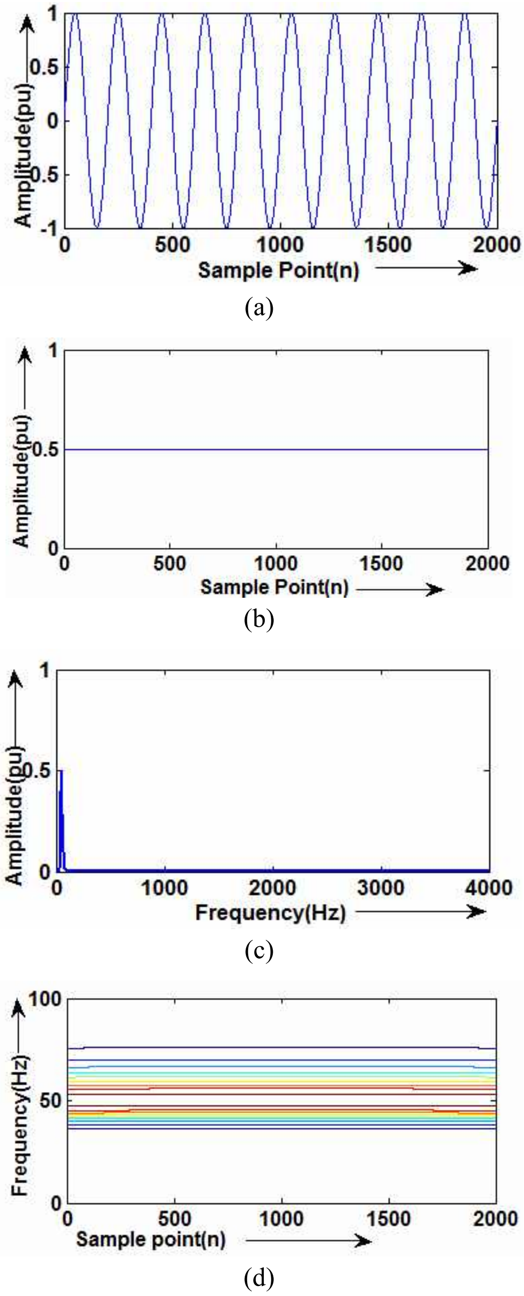


Fig. 1. STransform Characteristics of Normal Waveform (a) normal voltage signal (b) time-maximum amplitude plot (c) frequency-maximum amplitude plot (d) time-frequency contour

The statistical methods are applied to the N by M complex matrix obtained as the output of S-Transform to extract the features corresponding to power quality events. The rows and columns of the complex matrix obtained as output from S-Transform represent frequency and time respectively. [14]

In the present work S-transform is applied to extract features of eight power quality disturbance namely Sag (C1), harmonics(C2), Interruption(C3), Swell(C4), Swell with harmonics(C5), Sag with harmonics (C6), Flicker(C7)

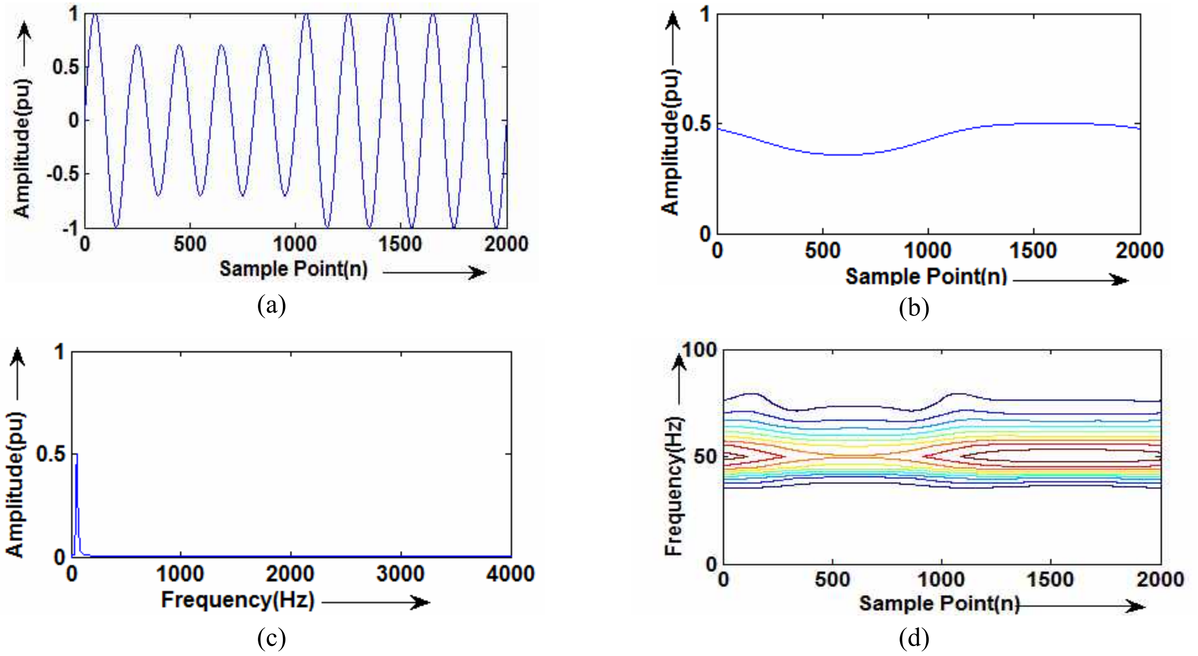


Fig. 2. S-Transform Characteristics of Sag Waveform (a) Sag signal (b) time-maximum amplitude plot (c) frequency-maximum amplitude plot (d) time-frequency contour

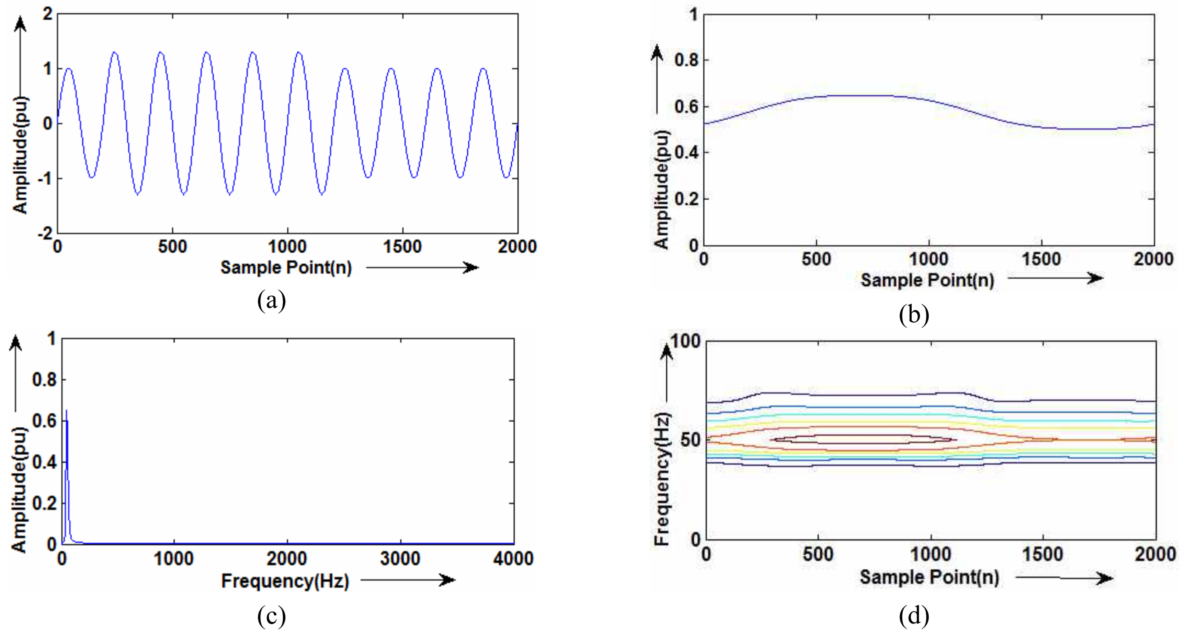


Fig. 3. S-Transform Characteristics of swell Waveform: (a) Swell signal (b) time-maximum amplitude plot (c) frequency-maximum amplitude plot (d) time-frequency contour

and Oscillatory Transient(C8). The waveforms are modeled in MATLAB using the equations reported in [14]. To highlight the capability of S-Transform in recognizing power quality events typical power quality disturbances are simulated in MATLAB and the results are depicted.

Fig. 1 shows the simulated normal voltage signal (a) along with the time maximum amplitude (TmA) plot (b) frequency maximum amplitude (FmA) plot (c) and time frequency contour (d). The time maximum amplitude plot represents maximum amplitudes versus time values. The values in these plots are determined by examining the columns of the S matrix at every frequency. The frequency amplitude plot represents maximum amplitudes versus normalized frequency values. The values in these plots are determined by examining the rows of the S-matrix at every frequency. The time frequency contours represent frequency values versus time values for the S-matrix. Figs. 2,3,4 illustrates these plots for sag, swell and interruption disturbances. From the figures it is evident that S-transform provides clear information about the type of power quality disturbances. For classification of disturbances the features should be extracted from time, frequency and amplitude. In addition the classification accuracy will be improved by incorporating the features extracted from high and low frequency areas separately. In this context a total of 20 features as shown in Table 1 are extracted for classification of power quality disturbances. These features have been obtained by programming in MATLAB/SIMULINK environment.

Table 1. Features for signal characterization

Feature F1-Maximum of TmA-plot
Feature F2-Minimum of TmA-plot
Feature F3-Mean of TmA-plot
Feature F4-Standard deviation of TmA-plot
Feature F5= abs(F1-F2-1/2)
Feature F6-Standarddeviation of the FmA-plot in the high frequency area above 100Hz.
Feature F7-Maximum amplitude of the FmA-plot in the high frequency area (AHFMax).
Feature F8-Minimum amplitude of the FmA-plot in the high frequency area (AHFMax).
Feature F9- F7-F8;
Feature F10-Kurtosis of the high frequency area.
Feature F11-Skewness of the high frequency area.
Feature F12-Mean of FmA-plot
Feature F13-Standard deviation of FmA-plot
Feature F14:Mean of the frequency standard deviation plot.
Feature F15-Standard deviation of the frequency standard deviation plot.
FeatureF16-Standarddeviationinthelowfrequency area, below100Hz, of the frequency standard deviation plot.
Feature F17-Standarddeviationinthehighfrequency area, above 100Hz, of the frequency standard deviation plot
Feature F18-Total harmonic distortion (THD).
Feature F19-Standard deviation of contour having the largest frequency amplitude of time frequency contour
Feature F20-Mean of contour having the largest frequency amplitude of time frequency contour

3. Fully Complex-Valued RBF Network

In this work a fully complex-valued RBF (FC-RBF) network with activation function sech(.) is used for classifying the power quality signals. The structure of fully complex RBF network is shown in figure 5. The network consists of input layer, hidden layer and output layer. Here X represents the complex valued input and the target is represented as T while the output of the network is represented as Y. The activation function of the hidden neuron is 'sech(.)' function[16].

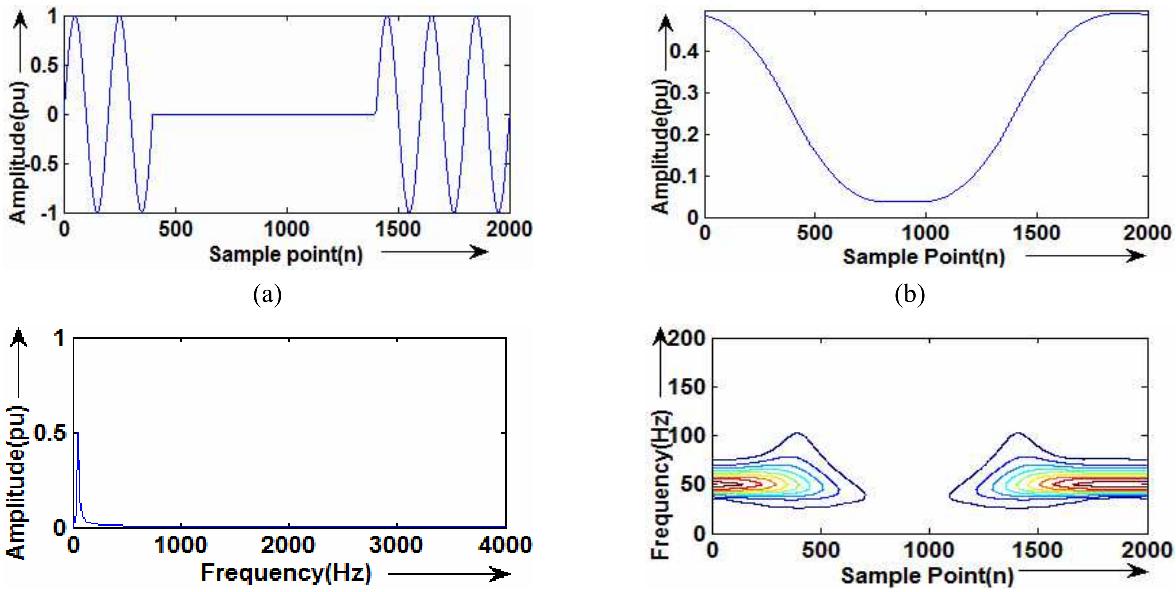
The hidden neuron activation function is described as

$$O_h^i = \operatorname{sech}(\underline{V}_i^T(\underline{X} - \underline{C}_i)), \quad i = 1, 2, ..., h. \tag{8}$$

where V_i, the complex-valued scaling factor and C_i, the center of the ith neuron. h indicates the number of hidden neurons. The scaling factor V_i is equivalent to the deviation σ in the real-valued gaussian function.

The output of the network Y_i is given by

$$Y_i = \sum_{j=1}^{h} W_{ij} O_h^i, \quad i = 1, 2, ..., n \tag{9}$$



(a) (b) (c) (d)

Fig. 4. STransform Characteristics of Interruption Waveform: (a) Interruption signal (b) time-maximum amplitude plot (c) frequency-maximum amplitude plot (d) time-frequency contour

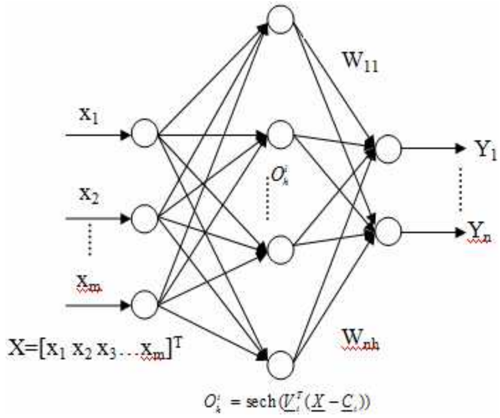


Fig. 5. Architecture of FC-RBF Classifier

where the W_{ij} are the complex-valued output weights.

The sum-squared error at the output layer is given by

$$E = \frac{1}{2}\sum_k (\|e_k\|^2); \tag{10}$$

where $e_k = T_k - Y_k$

If h is the number of neurons in the hidden layer, and $O_h^j = u_j + jv_j$ is the response of the jth hidden node,

$$Y_i = \sum_{j=1}^{h} W_{ij} O_h^i = \sum_{j=1}^{h} (W_{nj}^R + jW_{nj}^I)(u_j + jv_j) \tag{11}$$

The three parameters (W, C and V) of the network are updated using complex-valued gradient update rule and is given by

$$\Delta W_{nj} = \alpha \bar{O}_h^j \delta_n \tag{12}$$

$$\Delta V_i = \beta \delta_n \bar{W}_{nj} \bar{\phi}'(V_i^T(X - C_i))\left(\overline{X - C_i}\right) \tag{13}$$

and

$$\Delta C_i = -\eta \delta_n \bar{W}_{nj} \bar{\phi}'(V_i^T(X - C_i))\bar{V}_i \tag{14}$$

where α, β and η are the learning rate parameters. The learning rate parameters can be real, imaginary or complex.

4. Complex Extreme Learning Machine Network

Extreme Learning Machine(ELM) proposed by Hung et al is a single hidden layer feed forward network, where the input weights are selected randomly and the output weights are calculated analytically. The neurons in the hidden layer employ complex valued activation function sech(.) [17]

The output of the hidden layer is given by

$$y_h^j = \text{sech}\ (u_j^T(x_i - v_j));\ j = 1...K \tag{15}$$

where $u_j$is the complex-valued scaling factor and v_j is the center of the j-th neuron.

The output of the classifier is given by:

$$\hat{y}_l = \sum_{i=1}^{K} w_{lj} y_h^j,\ l = 1,...,C \tag{16}$$

where w_{lj} are the complex-valued weight between the l-th output neuron and the j-th hidden neuron.

The class labels are evaluated from the outputs using:

$$\hat{C} = \arg\max_{i=1,2,...C} real(\hat{y}_l) \tag{17}$$

Eq. (16) can be written in a matrix form as

$$\hat{Y} = WH \tag{18}$$

where W is the matrix of all output weights connecting the hidden layer, and H is the $K \times N$ matrix of the response of the hidden neurons for the samples in the training data set given by

$$H(V,B,Z) = \begin{bmatrix} \text{sech}(u_1\|z_1 - v_1\|) & \cdots & \text{sech}(u_1\|z_N - v_1\|) \\ \vdots & \vdots & \vdots \\ \text{sech}(u_K\|z_1 - v_K\|) & \ldots & \text{sech}(u_K\|z_N - v_K\|) \end{bmatrix} \tag{19}$$

Similar to the ELM, the parameters of the hidden neurons (u_j, v_j) are selected at random and the output weights W are estimated by the least squares method according to:

$$W = YH^{\dagger} \tag{20}$$

where $H^{\dagger}$ is the Moore-Penrose inverse of the hidden layer output matrix, and Y is the complex-valued coded class label. The complex ELM algorithm consists of the following steps:

1. Select the number of hidden neurons
2. Randomly choose the scaling factor U and the neuron centres V.
3. Analytically calculate the output weight (W).

5. Support Vector Machine(SVM)

The basis of Support Vector Machine (SVM) proposed by Vapnik [27] is statistical learning theory with significant features like nonexistence of local minima, sparseness of the solution, and the usage of kernel-induced feature spaces. In recent years SVM has been widely applied for pattern recognition and classification problems. The other machine learning classifiers separate classes using hyper planes, while SVM classifies non linear data by widening the hyperplane by mapping the predictors onto a new, higher-dimensional space in where they can be separated linearly [28].

The training set P for the support vector classifier is described as:

$$P = \{(x_i, y_i) \mid x_i \in \Re y_i \in \{-1,1)\}_{i=1}^{n} \tag{21}$$

where x_i represents an input feature vector containing k attributes of a training sample, while y_i is the desired output.

In SVM, the main objective is the formation of hyperplane to linearly separate data into two classes. There might be infinite number of hyperplane positioned between the two classes. SVM extends the hyperplane margin to accomplish good classifying performance

If the two classes are non-linear, a nonlinear transformation is introduced from input space to feature space of higher dimension.

$$\phi(x) : x \subset \Re^k \rightarrow \Re^m,\ k<<m \tag{22}$$

For the linearly separable hyperplanes the following function is applied,

$$f(x) = \sum_{i=1}^{n} w_i x_i + b \tag{23}$$

In order to attain linear separability in feature space, the hyperplane function must seek out for,

$$\begin{aligned} f(x) &= \sum_{i=1}^{n} w_i \phi(x_i) + b \geq 1 \quad \forall i : y_i = +1 \\ f(x) &= \sum_{i=1}^{n} w_i \phi(x_i) + b \leq 1 \quad \forall i : y_i = -1 \end{aligned} \tag{24}$$

To achieve linear separability of the two classes a soft-margin involving slack variables ξ_i is introduced as given by the following equation [29,30]

$$\Im(x, \xi) = \frac{1}{2} \sum_{i=1}^{n} w_i^2 + C \sum_{i=1}^{n} \xi_i \tag{25}$$

Subject to

$$y_i f(x) \geq 1 - \xi_i \quad \xi_i > 0 \tag{26}$$

The compromise between the training errors and generalization functionality is regulated with the aid of the parameter C. Large C reduces training misclassification, while a small C increases the misclassification..A kernel function often attributed to Mercer's theorem [29] is defined as the dot product of the nonlinear functions $\phi(\cdot)$.

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j) \tag{27}$$

The kernels suggested in literatures include linear, polynomial, gaussian radial basis function and sigmoid. In this work gaussian radial basis function is used as kernel function and is given by.

$$K(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma \left\| \mathbf{x_i} - \mathbf{x_j} \right\|^2) \tag{28}$$

The hyperplane function is rewritten as :

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b \right) \tag{29}$$

where $0 \leq \alpha_i \leq C$.

The SVM classification problem represented by equation (29) is solved if the Karush-Kuhn-Tucker (KKT) optimality criteria are satisfied for all α_i

$$\begin{aligned} y_i f(x_i) &> 1 \ if \ \alpha_i = 0 \\ y_i f(x_i) &< 1 \ if \ \alpha_i = C \\ y_i f(x_i) &= 1 \ if \ < \alpha_i < C \end{aligned} \tag{30}$$

To improve the classification accuracy of SVM, two important RBF parameters (C and γ) must be chosen suitably. Parameter C signifies the cost of the penalty which needs to be chosen carefully to improve the classification accuracy. Parameter γ influences the classification result as it affects the partitioning outcome in the feature space. In this work the value of C is chosen as 5 and γ is chosen as 4

6. Results and Discussion

This section discusses the results of FC-RBF classifier for recognizing power quality disturbances. The FC-RBF algorithm as discussed in[16] is used for evaluating the performance of the classifier. A total of 1100 samples of 8 classes of disturbance are simulated using Matlab software based on the models as specified in reference[14].The real time scenario is accounted by adding different levels of noise with signal to noise ratio 30,40 and 50 dB to the signals. Thus combining the ideal and noisy signals a total of 2933 signals are generated for training while 1465 signals are used for testing the performance of the classifiers. The training and testing classification results of FC-RBF and CELM without noise are presented in table 2 and 3 respectively. From the table it is seen that CELM marginally outperforms FC-RBF classifier.

Table 2 Training accuracy of complex classifiers without noise

Signal	FC-RBF	CELM
C1	99	100
C2	100	100
C3	100	100
C4	100	100
C5	100	100
C6	100	100
C7	100	100
C8	100	100

Table 3 Testing Accuracy of Complex classifiers without noise

Signal	FC-RBF	CELM
C1	100	100
C2	99	100
C3	100	100
C4	100	100
C5	100	100
C6	100	100
C7	100	100
C8	100	100

Table 4 Training Accuracy of Complex classifiers with different noise levels

	50 dB noise		40 dB noise		30 dB noise	
Signal	FC-RBF	CELM	FC-RBF	CELM	FC-RBF	CELM
C1	99	97	100	100	100	94
C2	100	100	100	100	100	97
C3	100	100	100	100	100	100
C4	100	99	100	99	100	100
C5	100	100	100	100	97	97
C6	100	100	100	100	100	100
C7	100	100	100	100	100	100
C8	100	100	100	100	100	97

Table 5 Testing accuracy of complex classifiers with different noise levels

	50 dB noise		40 dB noise		30 dB noise	
Signal	FC-RBF	CELM	FC-RBF	CELM	FC-RBF	CELM
C1	100	96	100	96	100	100
C2	100	100	100	100	100	97
C3	100	100	100	100	100	100
C4	100	100	100	100	100	100
C5	100	100	100	100	100	98
C6	100	100	100	100	100	100
C7	100	100	100	100	100	100
C8	100	100	100	100	94	97

Table 6 Classification Statistics of Complex classifiers

Algorithm	Root Mean Square	
	Training	Testing
FC-RBF	0.0037	0.0038
CELM	0.0362	0.0701

The training and testing classification results of FC-RBF and CELM with different levels of noise are presented in table 4 and 5 respectively. From the table it is evident that the FC-RBF classifier performs well under noisy conditions. In addition the convergence characteristics of the complex classifiers are analysed by computing the root mean square of training and testing error. The values depicted in table 6 indicate that the FC-RBF network has better convergence.

To further establish the efficiency of the classifier a comparison with real valued classifiers is performed. The overall training and testing accuracy of the classifiers is depicted in figure 6 and 7 respectively. From the results it is evident that the FC-RBF approach has a better classification accuracy in comparison with CELM, ELM and SVM respectively.

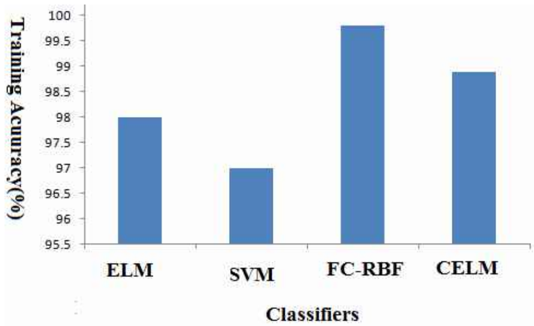


Fig. 6. Training Accuracy of Classifiers

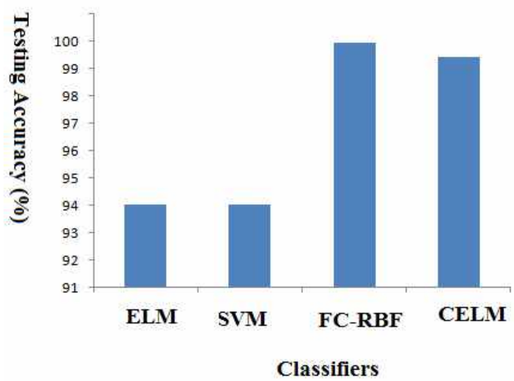


Fig. 7. Testing Accuracy of Classifiers

7. Conclusion

An approach for classifying power quality disturbances based on complex neural network is presented in this paper. The power quality signals are processed through time frequency transformation technique, S-Transform to extract the features. The extracted features form input to the FC-RBF and CELM network. The results reveal that the classification accuracy of FC-RBF is better under noisy conditions. In addition the root mean square of the training and testing error of both the algorithms are compared and results indicate the better convergence of FC-RBF. The performance of FC-RBF in comparison with real valued classifiers augurs well for its suitability in classifying real time power quality disturbances.

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