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Automated Classification and Detection of Power Quality Disturbances using RBF Fault Classifier

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Abstract*— the proliferation of power electronic devices in a modern industrial control pronounced more power quality disturbances. There is an urgent need of technique which automatically classifies and detects power quality disturbances. In this paper authors developed an online radial-basis-function NN-based detection technique. In proposed scheme simple statistical parameters described which are used as input noise signals to classify vital conditions of power system like sag, swell of Induction motor, arc load, short circuit of welding machine, phase to earth fault and healthy condition. Detailed design procedure for RBF based classifier is presented for which experimental data of one HP, single phase, 50 Hz squirrel cage Induction motor, Welding machine to generate actual arcing load, Advantech data acquisition system is used. A Wavelet Transform Technique is applied to extract features from monitored data. By principle component analysis and sensitivity analysis dimension reduction is also achieved which classify the six types of PQ disturbances.

Index Terms-Power Quality, Wavelet transform, RBF, PCA

I. INTRODUCTION

The absolute necessity to quantify electrical power quality is an ultimate result of application of deregulation policies adopt in electrical power system. The growing complexity of industrial processes as well as system interconnections lead to high inter-dependability, it may results in severe consequences such as huge economic losses. This fact highlights the need of good quality of power supply. In general, the term used to address this quality of supply is 'Power Quality' (PQ). Horizon of techniques emphasis on "minimum configuration intelligence" and "modelling" give rise to a technique where no detailed analysis of the fault mechanism is necessary, nor any modelling of the system required. In AI technique fault detection and evaluation can be accomplished without an expert. New techniques concern the choice and the mapping of the input and output data. Perspective of PQ problem covers a wide spectrum which involves harmonics, voltage sag, voltage swell and momentary interruptions.

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These disturbances cause problems such as overheating, motor failures, inaccurate metering and malfunctioning of protective equipment. It is important for further understanding and improving power quality to extract features of disturbances from a large number of power signals and to recognize them automatically. Researchers working in this domain adopted variety of methodologies for PQ analysis such as spectral content obtained as a function of time using
Fractional Fourier transform, Short Time Fast Fourier transform (STFT)[1], and wavelet transforms[2]-[4]. Additional wavelet coefficients with border distortions yield the real-time detection [5]. Relevant features of experimental data extracted using S-Transform (ST) algorithm and fuzzy decision inspired the researchers a lot [6]-[7].Rule base neural networks NN also act as a feature extraction tool [8]-[9]. Hilbert transform (HT)-based novel method of classification of PQ events implemented [10]. Spectral kurtosis (SK) is a statistical tool decides the characteristics of transient disturbances [11]. Another approach is to train the NN for on-line or off-line estimation of certain system parameters. The NN is trained to estimate system parameters under different fault conditions using appropriate inputs and outputs (and/or certain observed variables) of the system, in a supervised learning environment references [12]-[20].Wavelet and support vector machine logic to identify disturbances were presented in [21]-[22].

II. DATA COLLECTION

To detect and classify the PQ disturbances, the Neural Network based classifier is designed and optimised. In first step data collection on various experimental setups is carried out as shown in Fig.1.

Fig.1. Experimental Setup

In experimentation following PQ disturbances are considered,

1) Voltage Sag
2) Voltage Swell
3) Arcing load influence

4) Line to Ground Fault

Mains fed one HP, single phase, 50 Hz squirrel cage Induction motor made is used for analysis of sag as well as swell in the system by switching ON/OFF operation. 230V, single phase, 50Hz, Welding machine is used to generate actual arcing load influence in the system, Welding electrodes keep short to experience a short circuit phenomenon in the lab. The Tektronix Digital Storage Oscilloscope (DSO), TPS 2014 B, with 100 MHz bandwidth and adjustable sampling rate of 1GHz is used to capture the current signals. The Tektronix voltage probes of rating 1000 V, and bandwidth of 200 MHz approximately, 100 sets of signals were captured with a sampling frequency of 10 kHz, at different mains supply conditions. The experimental setup uses an Advantech data acquisition system having specification, as PCLD-8710 - 100 KS/s, 12-bit, 16-ch PCI Multifunction Card. Overall to create a weak system inside the laboratory 2 ½ core, 200meter long cable is used so that influence of sag, swell and arc load is distinct and will be observable, Thus all distinct and observable features are found as shown in fig (2) to fig (5).

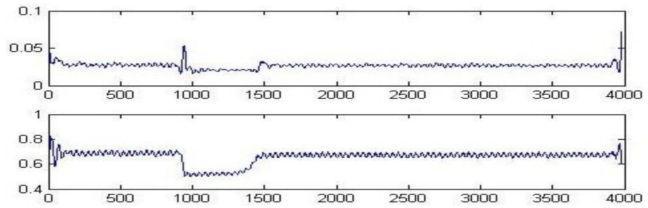

Fig.2. Sag due to Induction Motor start

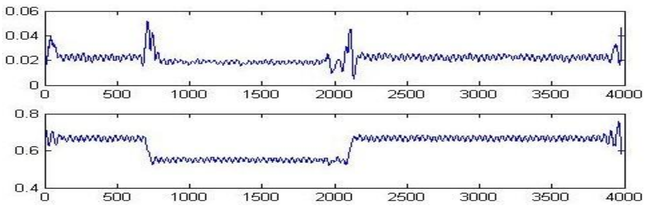

Fig.3. Sag due to Welding Machine short circuited

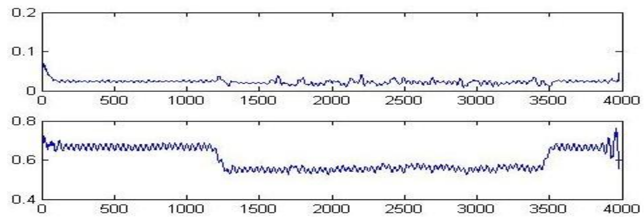

Fig.4. Sag due to Arc load of Welding Machine

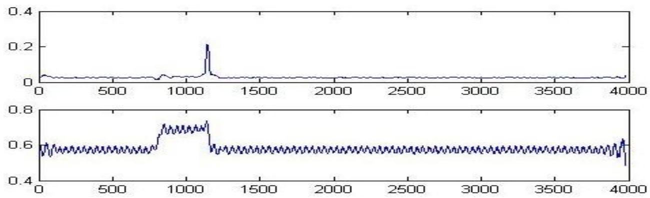

Fig.5. Swell due to Induction Motor off

Statistical parameters are used to classify the different power quality disturbances. To be precise, ‘sample’ statistics will be calculated for current data. Minimum set of statistical data to be examined which mainly includes the kurtosis coefficient, maximum and minimum values of the skewness coefficient and root mean square (RMS) of the zero mean signal (standard deviation), and, *Pearson's coefficient of skewness*, g_2 defined by:

$$g_2 = \frac{3(\bar{x} - \tilde{x})}{S_x} \qquad (1)$$

$\bar{x}$, x and S_x is mean, median sample and standard deviation respectively. The sample coefficient of variation v_x is defined by;

The sample coefficient of variation v_x is defined by;

$$v_x = \frac{S_x}{\bar{x}} \qquad (2)$$

Data set for the r^{th} sample moment about the sample mean is:

$$m_r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^r}{n} \qquad (3)$$

m_2 refers to spread about the center, m_3 denotes to skewness about the center, m_4 refers about amount of data massed at the center. The Second, third and fourth moments are used to define explicitly the sample coefficient of skewness, g_3 and the sample coefficient of kurtosis, g_4 as follows.

$$g_3 = \frac{m_3}{\left(\sqrt{m_2}\right)^3} \qquad (4)$$

$$g_4 = \frac{m_4}{\left(\sqrt{m_2}\right)^4} \qquad (5)$$

The covariance between dimensions j and k sample is given as;

$$c_{jk} = \frac{\sum_{i=1}^{n} \left(x_{ij} - \overline{x_j}\right)\left(x_{ik} - \overline{x_k}\right)}{(n-1)} \qquad (6)$$

For dimensions j and k, r_{jk} the ordinary correlation coefficient is given as;

$$r_{jk} = \frac{c_{jk}}{S_j - S_k} \qquad (7)$$

III. RBF NEURAL NETWORK

Radial basis function (RBF) networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements (PEs). This layer uses gaussian transfer functions, rather than the standard sigmoidal functions. The centers and widths of the gaussians are set by unsupervised learning rules, and supervised learning is applied to the output layer. These networks tend to learn much faster than MLPs. Use of this network is recommended only when the number of exemplars is so small (<100) or so dispersed that clustering is ill-defined.

For standard RBF's, the supervised segment of the network only needs to produce a linear combination of the output at the unsupervised layer. Therefore 0 hidden layers is the default. Hidden Layers can be added to make the supervised segment a MLP instead of a simple linear perceptron. Six conditions of PQ disturbances namely Healthy, Sag due to Induction Motor, Swell due to Induction

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Motor, Welding machine short circuit, Arc load and Line to Ground. For data processing XLSTAT-2008, MATLAB7.1, and Neuro Solution 5.0 are used.

The general learning algorithm is as follows:

For all value of x the response of Gaussian activation function is nonnegative. The function is defined as

$$f(x) = \exp(-x^2) \tag{8}$$

and its derivative

$$f'(x) = -2x\exp(-x^2) = -2f(x) \tag{9}$$

Back propagation network in the Gaussian function is different from the radial basis function.

Step 1: Initialize the weights (set to small values)

Step 2: do step 3-10, if stopping condition is false

Step 3: do step 4-9 for each input

Step4: all units in the hidden layer receives input signals from each input unit (x_i , $i=1,\ldots,n$) .

Step 5: Calculate the radial basis function

Step 6: Choose the centers for the radial basis functions. The centers are chosen from the set of input vectors. A sufficient numbers of centers have been selected in order to ensure adequate sampling of the input vector space.

Step 7: The output of i_m unit $v_i(x_i)$ in the hidden layer

$$v_i(x_i) = e\left\{\sum_{j=1}^{r} \frac{\left[x_{ji} - (x'_{ji})^2\right]}{\sigma_i^2}\right\} \tag{10}$$

Where x_{ji} - centre of the RBF unit for input variable

x'_{ji} - j^{th} variable of input pattern

σ_i -Width of the i^{th} RBF unit

Step 8: Initialize the weights in the output layer of the network to some small random value

Step 9: output calculation of the neural network

$$y_{net} = \sum_{i=1}^{H} w_{im} v_i(x_i) + w_0 \tag{11}$$

Where

H-number of hidden layer nodes (RBF Function)

y_{net} -Output value of m^{th} node in output layer for the n^{th} incoming pattern

w_{im} - Weight between i^{th} RBF unit and m^{th} output node

w_0 - Biasing term at n^{th} output node

Step 10: Calculate the error and check the stopping condition

To remove biasing and ensure true learning and generalization for different parameters, randomized data is retrained five times with different random weight initialization then fed to the neural network.

A. Selection of Error criterion:

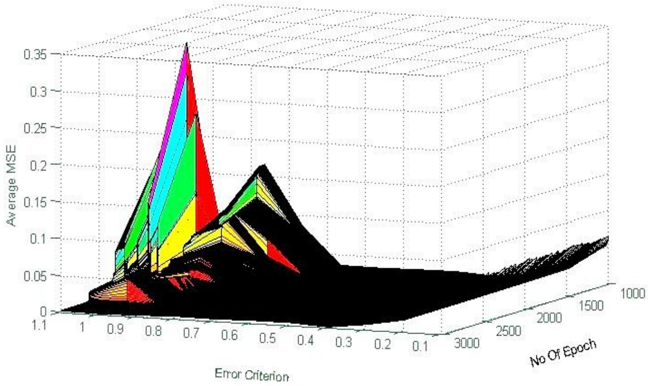
A supervised learning requires a metric to measure how the network is doing. Members of the Error Criteria compare with some desired response. Any kind of error reported to the appropriate learning procedure. Calculating the sensitivity proper metric is determined by using gradient descent learning. As the network approaches to the desired response Cost function, J should decay towards zero, but normally it is positive. In literature several cost functions has presented, in which p is define as p=1, 2, 3, 4… ∞ criterion is L-1, L-2, L-3, L-4 …L∞ Cost function is used to define Components in the Error Criteria family

$$J(t) = \frac{1}{2}\sum_i (d_i(t) - y_i(t))^p \tag{15}$$

and errors function:

$$e_i(t) = -(d_i(t) - y_i(t)) \tag{16}$$

As desired response and network's output are d (t) and y (t) respectively, various error criterions has been tested to select the correct error criterion and finally and results are given as in Fig. 6, Fig.7 and Fig. 8. Finally L-4 criterion gives the optimal results.



Y: Error Criterion X: No. of Epochs

Fig.6. Average MSE with Error Criterion

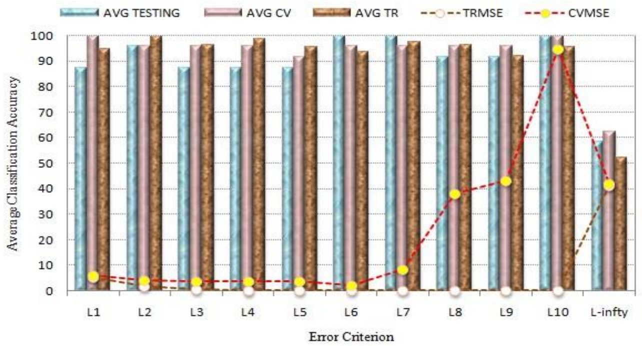


Fig.7. Average Classification Accuracy with Error Criterion

From the experimentation the unsupervised and supervised parameters, competitive rule, metric and cluster centers have been selected. Experimentation results are shown in Fig.6. to Fig.10.

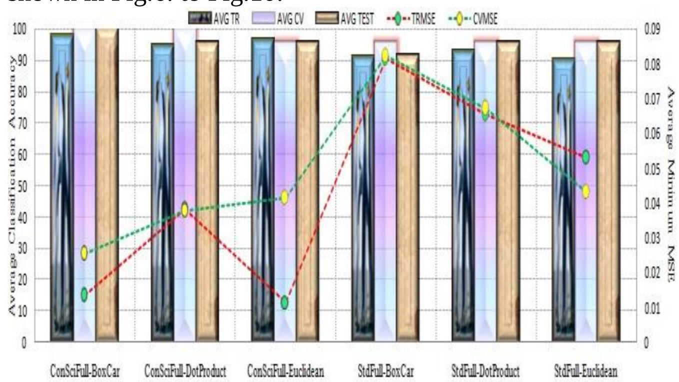


Fig.8. Average Classification Accuracy with Competative rule and metric

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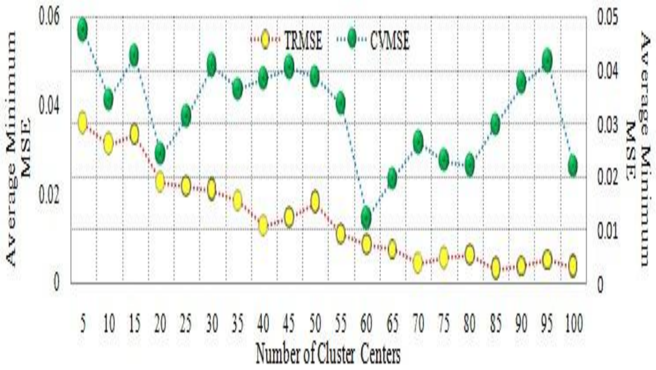

. **Fig.9. Average Minimum MSE for different number of Cluster Centers**

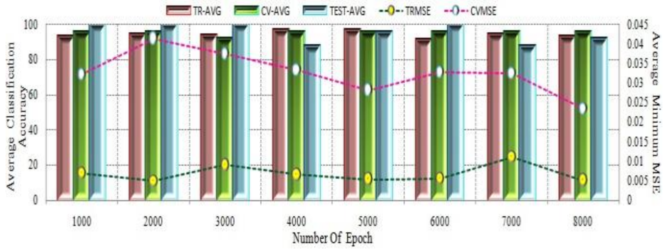

Fig.10. Average Classification Accuracy and Average minimum MSE with Epoch

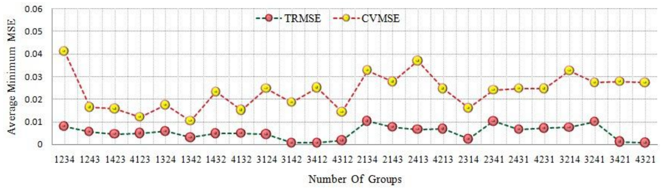

Fig.11. Average Minimum MSE with Training and CV for group of Dataset

Finally, the RBF classifier is designed with the following parameters:

Number of Inputs: 14

Competitive Rule: Conscience-Full, Metric: Boxcar,

Number of Hidden Layers: 0

Output Layer: Learning Rule: Momentum,

Step Size: 0 .100 Momentum: 0.7000

Transfer Function: Tanh

Number of epochs = 5000

Unsupervised Learning: Maximum Epoch: 1500

Supervised Learning: Maximum Epoch: 3500

Learning Rate: start at: 0.01 Decay to: 0.001

Number of Cluster Centers: 60

Number of connection weights: 1266

Exemplars for training = 70%,

Exemplars for cross validation = 15%

Exemplars for Testing = 15%

Time required for RBF is 0.604 micro-secs

Using variable split ratios and leave-N-out cross validation technique, different datasets are formed. On these datasets proposed NN is trained and tested five times. Training and testing data validated carefully to ensure its performance. It does not depend on specific data partitioning scheme. The performance of the NN should be consistently optimal over all the datasets with respect to MSE and its classification accuracy. Total data is divided in four groups to check the learning ability and classification accuracy. 50% data are tagged as Training data for first two groups and 25% is tagged for third and forth group (each for Cross Validation and Testing (1234: 1&2-TR, 3-CV, 4-Test).Network is train and test for 24 combinations. Results are shown Fig.11 to Fig.13.

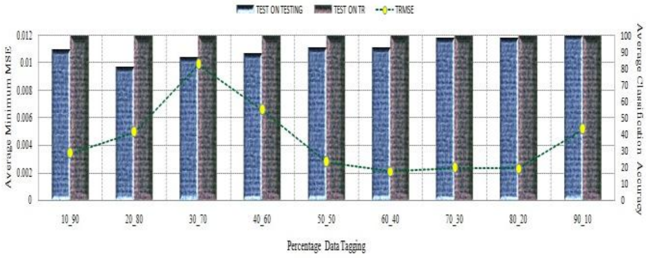

Fig. 12. Average Classification Accuracy with testing on Testing and Training dataset and percent data tagged for training

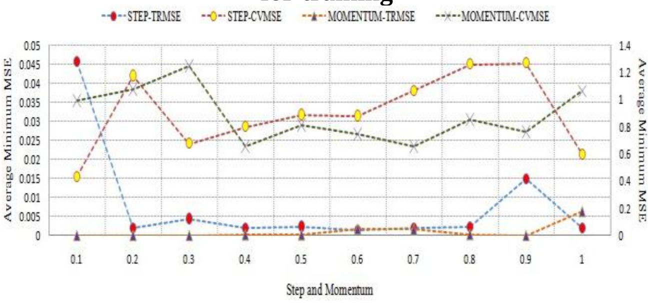

Fig. 13. Average Minimum MSE with Training and CV for Step and Momentum

IV. DIMENSION REDUCTION

A. Sensitivity Analysis

One difficulty always comes into sights that, after the feature extraction too many input features are come out. They would require significant computational efforts for calculation and results in low accuracy. To reduce the number of inputs and dimensions of the network model, the sensitivity analysis is performed as shown in Fig.14.

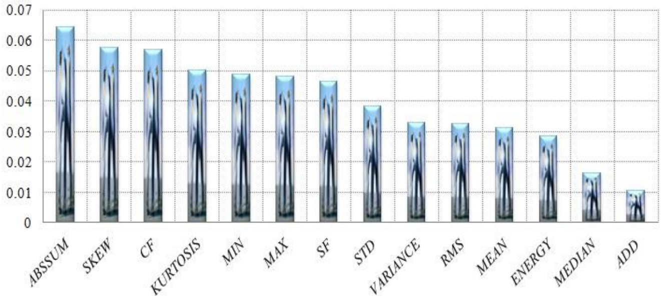

Fig. 14. Sensitivity Analysis

From the analysis, most sensitive parameters are selected as input parameters. Number of input parameters most sensitive in descending order verses average minimum MSE on training and cross validation is as shown in Fig. 15 and average classification accuracy is shown in Fig. 16.

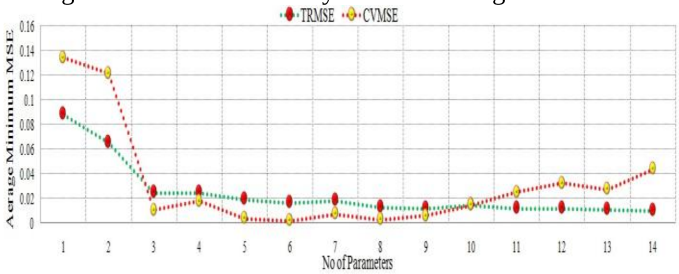

Fig. 15. Change over average minimum MSE on

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training and CV dataset with number of inputs

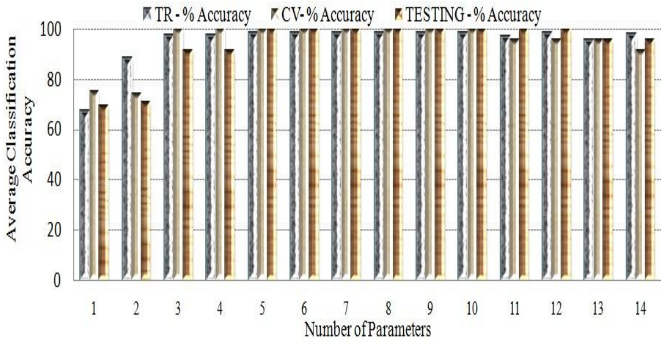

FIG. 16. AVERAGE CLASSIFICATION ACCURACY WITH TEST ON TESTING, CV AND TR DATA WITH NUMBER OF INPUTS

Using the results of sensitivity analysis, dimensions of RBF network can be reduced. Numbers of inputs are reduced to eight. By similar experimentations, the optimum RBF classifier is designed with the following changes;

Competitive Rule: Conscience Full   Metric: Euclidean

Number of cluster centers: 45

Number of inputs: 8

Number of connection weights: 681

Number of connection weights reduced by: 46.20%

Time required for RBF-DR-S (Dimensionally Reduced using sensitivity analysis) is 0.2683 micro-secs

Finally, the new RBF (RBF-DR-S) classifier is trained and tested for various conditions.

B. Principal Component Analysis

Principal Component Analysis (PCA) is used to reduce dimensionality of the input space and hence the reduced network can be achieved. PCA is performed by Pearson rule. Fig.17 is allied with a mathematical object, the Eigen values, which reveal the quality of the projection to a lowest number of dimensions.

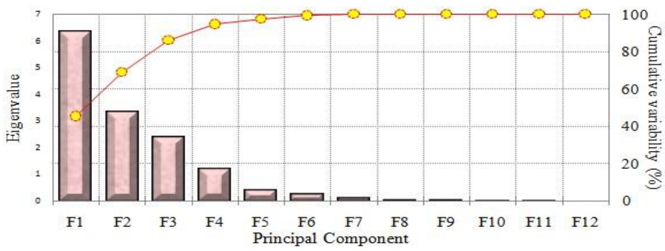

Fig. 17. Principal Component, Eigen values and percent variability

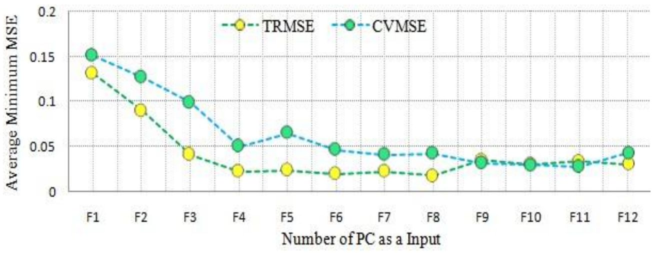

Fig. 18. Average minimum MSE on training and CV dataset with number of PCs as inputs

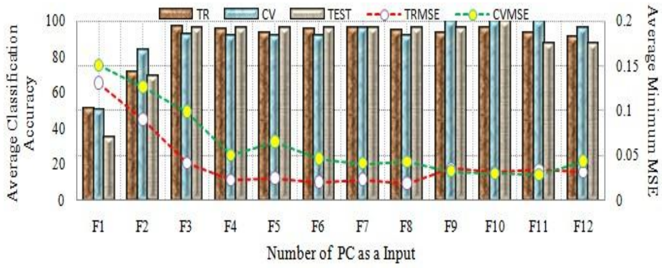

Fig. 19. Average classification accuracy with test on Testing, CV and TR Data with number of PCs as inputs

By these experimentations, the optimum RBF classifier is designed with the following changes;

Number of Inputs: 7

Competitive Rule: Standard Full   Metric: Boxcar

Number of Hidden Layers: 0

Output Layer:

Transfer function: tanh   Learning Rule: step

Number of cluster centers: 45

Number of inputs: 7

Output Layer: Step Size: 0 .5

Learning Rate Start at: 0.01   Decay to: 0.001

Number of connection weights: 636

Number of connection weights reduced by: 49.76%

Time required for RBF-DR-PCA (Dimensionally Reduced using PCA) is 0.4600 micro-secs

Finally, the new RBF (RBF-DR-PCA) classifier is trained and tested for various conditions.

V. CONCLUSIONS

In recent time, maintaining power quality standards had been a major concern for electric utilities. Researchers in power quality domain confronted a challenge of accurately analyzing the disturbances in it. Transform techniques like discrete and fast fourier transform gave a basic tool for this purpose. However, to overcome limitations of these transform techniques in case of non-stationary signals, windowed techniques like Wavelet and S-transform, which suits better for feature extraction of waveforms were implemented. Recent approaches implement the artificial intelligence techniques for automating the analysis process. Techniques like artificial neural network and fuzzy logic in combination with mathematical tools improved the diagnostic accuracy to a remarkable level. Also application of optimization tool like genetic algorithm helped to optimize the process parameters and hence further improvement of accuracy.

VI. RESULTS AND DISCUSSION

In this paper, the authors appraised the performance of the developed RBF NN based classifier for detection of six conditions of power quality disturbances and examined the results. The network learned is capable to detect different types of disturbances after completion of the training, Various learning rules and transfer functions are investigated.. Combination of Conscience Full Competitive Rule and Boxcar metric gives the best results. Initially, MSE goes on decreasing with increase in number of cluster centers and it attains minimum value at 60 cluster centers, beyond which it is observed that there is no significance

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decrease in MSE. By performing Sensitivity analysis and Principal Component Analysis, numbers of inputs are reduced from 14 to 8 and 14 to 7 respectively. Numbers of cluster centers are also reduced from 60 to 45 for both. Number of connecting weights are also highly reduced from1266 to 681(46.20%) and 1266 to 636 (49.76%) respectively. This shows explicitly a dimension reduction at a great extend. From the analysis, it is seen that dimensionally reduced, using PCA and RBF (RBF-DR-PCA) based classifier works as an elegant classifier for diagnosis of six typical power quality disturbances, in the sense of that, average MSE on samples is consistently observed to be reasonable such as 0.0015185. In addition, average classification accuracy is obtained as 98.05% indicating a reasonable classification.

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