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AUTOMATIC RECOGNITION SYSTEM FOR POWER QUALITY DISTURBANCES BASED ON WAVELET AND ANN

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Abstract- Modern electrical loads heavily impregnated with sensitive electronic equipment. These so called modern loads are normally known as nonlinear loads. An exponential increase in such loads in power-system hampered the quality of power supply. Hence, power quality disturbances are present almost in every electrical system. Deterioration in quality of power termed as Power Quality (PQ) Disturbance. These PQ disturbances are the main cause behind often occurred Electrical disturbances. This paper proposed a Multilayer Perceptron Neural Network based classifier with simple statistical parameters which are used as input noise signals to classify frequently occurred PQ disturbances. Sag, swell of Induction motor, arc load, short circuit of welding machine, phase to earth fault and healthy condition for effective classification of power quality disturbances are considered. For feature Extraction Wavelet Transform Technique and experimental data of one HP, single phase, 50 Hz squirrel cage Induction motor, Welding machine to generate actual electrical arc, Advantech data acquisition system is used. Optimized NN base classifier classifies six types of the PQ disturbances with accuracy of 99.18%.

Keywords: Power Quality, Fourier Transform, Wavelet Transform, Artificial Intelligence, Neural Network.

I. INTRODUCTION

Modern era is expecting a large productivity and high efficiency with rapidly increasing end users as well as proliferated nonlinear loads. Extensive use of sensitive automated power electronics equipment deviates supply from its normal values. Ultimately it effects on the growing interconnected systems, thus results in severe consequences such as huge economic losses if any component fails. Hence 'Power Quality' becomes a buzz word in Electrical Power System. Horizon of PQ problem covers a wide spectrum which involves harmonics, voltage sag, voltage swell and momentary interruptions [1]. 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 power signals and to recognize them automatically. Researchers working in this domain adopted variety of methodologies for PQ analysis such as fast Fourier transform (FFT) [2], fractional Fourier transform [3] and wavelet transform [4-7]. Extraction of relevant features using S-Transform algorithm and fuzzy decision also inspired researchers a lot [8-10].Some fuzzy oriented research also reported [11-12].

Hilbert transform (HT)-based novel method of classification of PQ events implemented [13]. 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 [14-20].

II. DIAGNOSIS OF PQ DISTURBANCES

Fast diagnosis of PQ disturbances is an urgent requirement so as to assist network operators to performing counter measures. It also ensures the implementation of suitable PQ mitigation actions. To analyze power signals, various signal processing techniques such as Fourier transformation methods, wavelet transform and S-transform are commonly applied. Also, artificial intelligence (AI) techniques have found their application in this field of power system. Application of hybrid methodology by embedding above two techniques for diagnostic purposes is also successfully practiced by some researchers. This section further discusses each of these methodologies.

A. Fourier Transform (FT)

Convoluted periodic functions are written as the sum of simple waves, mathematically symbolized by sine and cosines and analysis for PQ are as follows:

i) Discrete Fourier Transform (DFT): Fourier Transform applied mostly to repetitive signals, often known as Discrete Fourier Transform. For a finite length discrete signal $x(n)$, it's DFT and frequency function is specified as in Equations (1) and (2), respectively.

$$X(f)=\frac{1}{N}\sum_{n=0}^{N\text{-}1} x(n)\mathrm{e}^{\frac{-j2\pi nf}{N}} \tag{1}$$

$$x(n)=\sum_{n=0}^{N\text{-}1} X(f)\mathrm{e}^{\frac{j2\pi nf}{N}} \tag{2}$$

ii) Fast Fourier Transform (FFT): FFT has an immense possibility in digital signal processor to provide a frequency spectrum analysis. In 1948, Cooley and Tukey exhibited the computation of N point DFT as a function of only $2N$ instead of N^2. Signal $x(n)$ decomposed into odd and even part using FFT can be written as,

$$FFT(x,y)=\frac{1}{2N}\sum_{n=0}^{N-1}x(2n)\mathrm{e}^{\frac{-\pi(2n)f}{N}}+\frac{1}{2N}\sum_{n=0}^{N-1}x(2n+1)\mathrm{e}^{\frac{-\pi(2n+1)f}{N}} \tag{3}$$

FFT reduces the computational complexity from N in DFT to $N\log N$ multiplications for same expression. This is a main advantage of FFT over DFT.

iii) Short Time Fourier Transform (STFT): It is use to analyze signals whose spectrum changes over a time. It is calculated by repeatedly multiplying the time series with shifted short time windows and performing a DFT on it. Here the window helps to localize the time-domain data before getting the frequency domain information. STFT for continuous time signal is given as;

$$X(\tau,\omega)=\int_{-\infty}^{\infty} x(t)\omega(t-\tau)\mathrm{e}^{-j\omega t}dt \tag{4}$$

where, $x(t)$ *is* signal to be transformed, $w(t)$ is window function, $X(\tau,\omega)$ is FT of $x(t)\omega(t-\tau)$. In case of discrete signal with m as discrete time-shift, it can be expressed as,

$$X(m,\omega)=\sum_{n=-\infty}^{\infty} x(n)w(n-m)\mathrm{e}^{-j\omega n} \tag{5}$$

However, STFT of a signal has constant window length which limits non-stationary signal resolution. To overcome this resolution problem using STFT, a signal processing tool, Wavelet Transform (WT), had been widely implemented in PQ analysis [23].

B. Wavelet Transform

In Wavelet Transform any signal is decompose for detailed analysis with multiple time–frequency resolution. Unlike STFT, the length of the smoothing window of the WT depends on the frequency analyzed. WT is commonly observed in mainly two forms namely: Continuous wavelet transform (CWT) and Discrete wavelet transform (DWT). The CWT is given by,

$$XWT(\tau,s)=\frac{1}{\sqrt{s}}\int x(t)\Psi\left(\frac{t-\tau}{s}\right)dt \tag{6}$$

where, $x(t)$ is signal to be analyzed, $\Psi(t)$ is the mother wavelet, s and τ represent scale and translational parameters, respectively. The DWT is a discrete counter of CWT for decomposition of the signal into mutually orthogonal set of wavelets. The WT follows some defined rules by means of a discrete set of the wavelet scales and translations [21-22].

C. Artificial Intelligence (AI)

ANN is self-learning computational system in the area of artificial intelligence, hence along with conventional training algorithms, an approach for hybrid algorithms as well as combined approach of ANN with wavelet and s-transform had been adopted. ANN has capability of non-linear function approximation and had been widely implemented in this domain. For industrial applications and recent concepts like distributed generation, ANN has found its application for PQ analysis and improvement.

III. DESIGN AND OPTIMIZATION OF NN BASED CLASSIFIER

A. Data Collection

To detect and classify the PQ disturbances, the Neural Network based classifier is designed and optimized. In first step for data collection experimental setup is shown as Figure 1.

Figure 1. Experimental setup

In experimentation following PQ disturbances are considered,

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

Mains fed one HP, single phase, 50 Hz squirrel cage induction motor made is used for analysis of sag as well swell in the system by switching ON/OFF operation. The 230 V, single phase, 50 Hz, 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 1 GHz 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, 200 m long cable is used so that influence of sag , swell and arc load will be observable.

B. Feature Extraction

Collected data is analyzed in MATLAB environment and using wavelet transform, its required features obtained.

To demonstrate feature extraction capability of the wavelet by MRA technique, three types of disturbances like Induction motor sag, arc load sag, and sag due to welding machine short circuit and swell due to Induction motor switching off along with their important features are presented. For decomposition and reconstruction of measured signal WT uses two function i.e. Wavelet function ψ and scaling function ϕ perform successive decomposition of signal by MRA technique. Wavelet function ψ serving as high pass filter and generates high frequency component known as detailed function (d) and scaling function ϕ is convolving the signal with a low pass filter which generates low frequency components known as approximate function (a) of decomposed signal as shown in Figures 2 to 5.

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 signals (standard deviation), and, Pearson's coefficient of skewness, g_2 defined by:

$$g_2 = \frac{3(\bar{x} - \tilde{x})}{S_x} \tag{7}$$

where $\bar{x}$, $\tilde{x}$, 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;

$$v_x = \frac{S_x}{x} \tag{8}$$

Data set for the *r*th sample moment about the sample mean is:

$$m_r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^r}{n} \tag{9}$$

where, m_2 refers to spread about the center, m_3 denotes to skewness about the center and 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.

$$g_3 = \frac{m_3}{\sqrt{m_2}^3} \tag{10}$$

$$g_4 = \frac{m_4}{\sqrt{m_2}^4} \tag{11}$$

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

$$c_{jk} = \frac{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{(n-1)} \tag{12}$$

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

$$r_{jk} = \frac{c_{jk}}{S_j - S_k} \tag{13}$$

C. Classifier Using MLP

Multilayer Perceptron (MLP) is layered feed forward networks typically trained with static back propagation. In Proposed classifier 14 number of input Processing Elements (PE) are used in input layer. In output layer Six Processing Elements are used for six conditions like sag, swell of Induction motor, arc load, short circuit of welding machine, phase to earth fault and healthy condition.

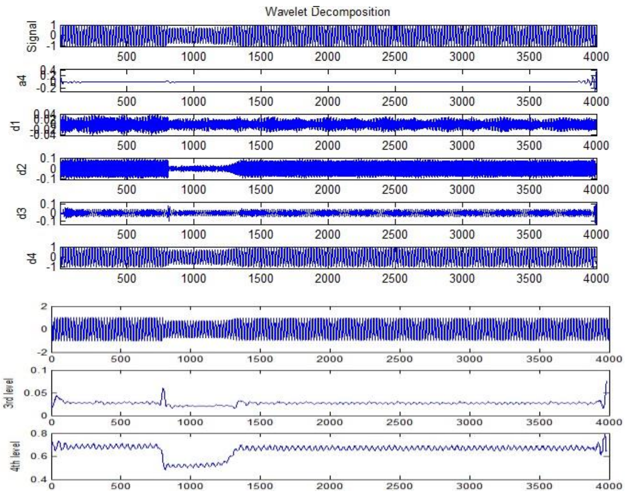


Figure 2. Sag due to induction motor starting

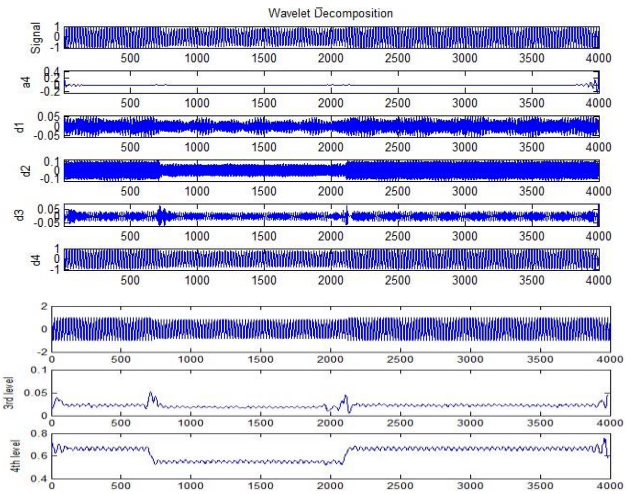


Figure 3. Sag due to welding machine short circuited

XLSTAT-2008, Neuro Solution 5.0 and MATLAB7.1 environment is used for processing of monitored data. General learning algorithm is as shown below:

Weights Initialization:

Step 1: Weights are Initializing to small random values

Step 2: Do step 3-10, while stopping condition is false

Step 3: Follow the steps 4-9 for each training pair

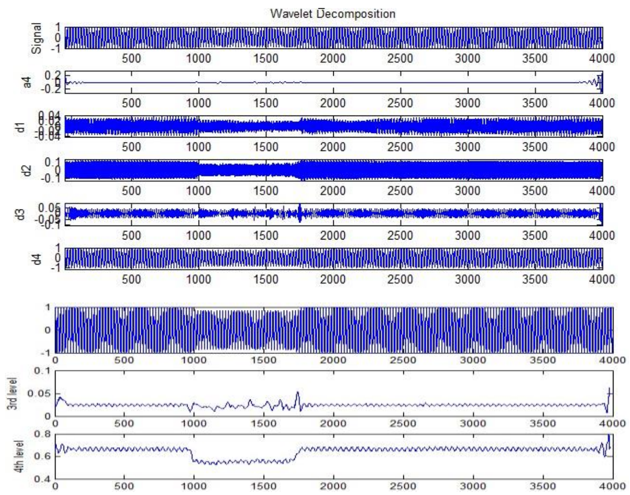


Figure 4. Sag due to arc load of welding machine

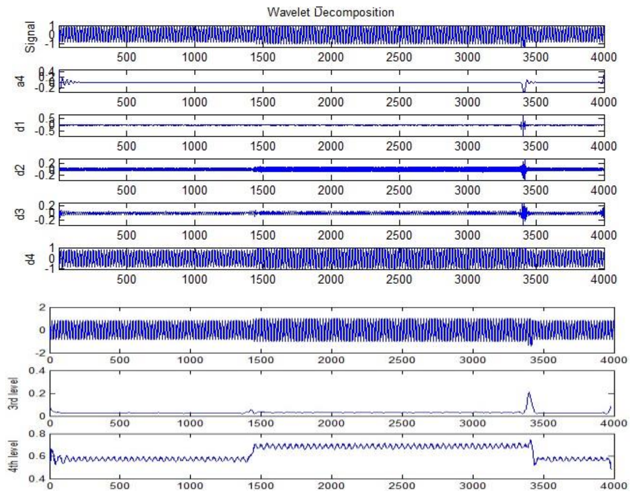


Figure 5. Swell due to induction motor off

Feed Forward:
Step 4: Transmit input signal x_i to all units in the hidden layer receives from each input
Step 5: Sums weighted input signals to each hidden unit $(z_j,\ j=1,\dots,p)$.

$$z_{-inj} = v_{aj} + \sum_{i=1}^{n} x_i v_{ij} \tag{14}$$

Activation function $Z_j = f(z_{inj})$ and function $\tanh(x)\tanh(x)=(e^x\text{-}e^{-x})/(e^x+e^{-x})$ send to all units of output units.
Step 6: Output of each unit $(y_k,\ k=1,\dots,m)$ sums its weighted input signals,

$$y_{-ink} = w_{ok} + \sum_{j=1}^{p} z_i w_{jk} \tag{15}$$

Now, applying its activation function for calculation of the output signals $Y_k = f(y_{-ink})$ here activation function is

$$\tanh(x)\tanh(x)=(e^x\text{-}e^{-x})/(e^x+e^{-x}) \tag{16}$$

Back Propagation Error:
Step 7: Each output unit $(y_k,\ k=1,\dots,m)$ receives a pattern of target corresponding to an input pattern error information hence this term is calculated as

$$\delta_k = (t_k - y_k)\, f(y_{-ink})$$

Step 8: Each hidden unit $(z_j,\ j=1,\dots,p)$ from units in the layer above sums its delta inputs

$$\delta_{-inj} = \sum_{k=1}^{m} \delta_i w_{jk} \tag{17}$$

The error information term is calculated as

$$\delta_j = \delta_{-inj}\, f\left(z_{-inj}\right) \tag{18}$$

Weight and Biases Updating:
Step 9: Output of each unit $(y_k,\ k=1,\dots,m)$ updates its bias and weights $(j=1,\dots,p)$

$$w_{jk}(t+1) = w_{jk}(t) + \alpha\delta_k z_j + \mu\left[w_{jk}(t) - w_{jk}(t-1)\right] \tag{19}$$

where α learning is rate and μ is momentum factor and each hidden unit $(z_j,\ j=1,\dots,p)$ updates its bias and weights $(i=1,\dots,n)$

$$v_{jk}(t+1) = v(t) + \alpha\delta_j x_i + \mu\left[v_{ij}(t) - v_{ij}(t-1)\right] \tag{20}$$

Step 10: Test the stopping condition

Randomly, different weights are used to retrain randomized data five times and then fed it to neural network. Initialization is so as to remove biasing and ensure true learning and generalization for different hidden layers. It is observed that MLP with single hidden layer provides better performance.

All eight Transfer function in combination with all six Learning rules are examined. Out of all combination best five are considered and results of transfer function Tanh Axon with Step Learning rule is found to be most effective as shown in Figure 6.

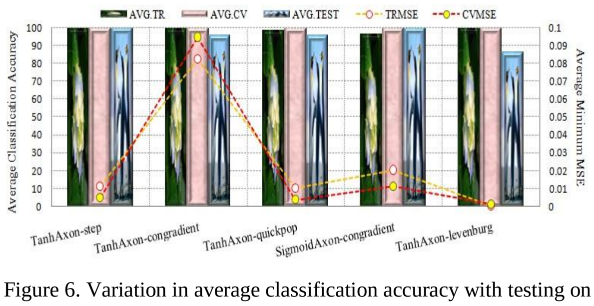
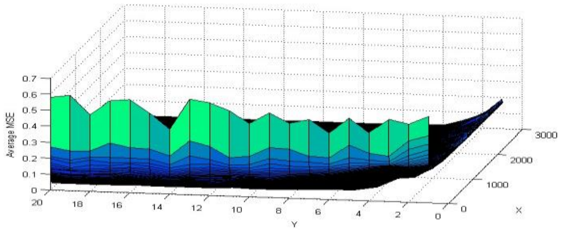


Figure 6. Variation in average classification accuracy with testing on training, CV and testing dataset and learning rule

The number of Processing Elements (PEs) in the hidden layer is varied. The network is trained and minimum MSE is obtained when 11 PEs are used in hidden layer as indicated in Figure 7.

Step size is Parameters of hidden layer and output layer. Step size is selected by comparing with Average minimum MSE and Optimum value of step size appears to be 0.8 in hidden layer and 0.9 in output layer. Performance is shown in Figure 8.



Y: Number of Processing Elements X: No. of Epochs

Figure 7. Variation of average minimum MSE with number of processing elements in hidden layer

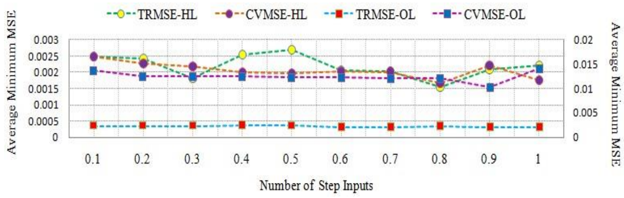


Figure 8. Variation in average minimum MSE with number of step inputs for hidden layer and output layer

Finally, the ANN classifier is designed with the following parameters:
Transfer: Tanh Axon Learning Rule: Step
Number of Inputs: 14
Number of Hidden Layers: 01
Number of PEs in Hidden Layer: 11
Hidden Layer:
Number of epochs = 4500
Transfer function: tanh Learning Rule: step
Step size: 0.8
Output Layer:
Transfer function: tanh Learning Rule: step
Step size: 0.9
Number of connection weights: 237
Training Exemplars = 70%,
Cross validation Exemplars = 15%
Testing Exemplars = 15%
Time required per epoch per exemplar: 0.1822 micro-secs
Selection of Error criterion:

To evaluate working of network supervised learning requires a metric. Comparing the members of the Error Criteria with some desired response, report any error to the appropriate learning procedure. The metric is determined by calculating the sensitivity using gradient descent learning. Cost function, J, is normally positive, but should decay towards zero as the network approaches the desired response. 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∞

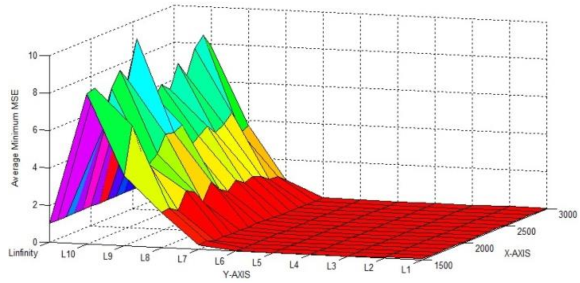
Error Criteria family components are defined by a cost function in the form:

$$J(t) = \frac{1}{2}\sum_i (d_i(t) - y_i(t))^p \tag{21}$$

and error functions:

$$e_i(t) = -(d_i(t) - y_i(t)) \tag{22}$$

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 L-2 criterion shown in Figure 9, gives the optimal results.



Y: Error Criterion X: No. of Epochs

Figure 9. Variation in average minimum MSE for error criterion

Leave-N-out cross validation and variable split ratios techniques are used to invent different datasets. 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 definite data partitioning scheme. The performance of the NN should be consistently optimal over all the datasets with respect to classification accuracy and it's MSE. Total data is divided in four groups to check its classification accuracy and learning ability. 50% data is 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). The network is train and test for 24 combinations. Results are shown in Figure (10) and Figure 11.

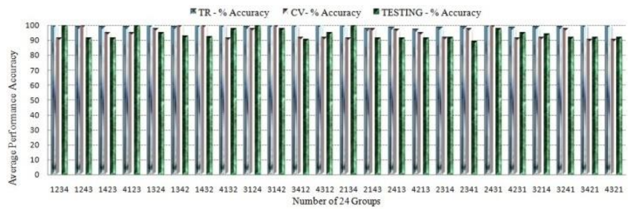


Figure 10. Variation in average classification accuracy with testing on training, CV and testing for all 24 group of dataset

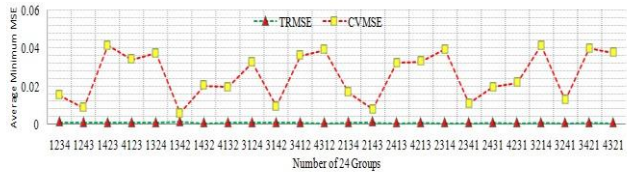


Figure 11. Variation in average minimum MSE with training and CV with 24 group of dataset

Variation in Average Classification Accuracy with testing on Testing and Training dataset as well as percent data tagged for training is shown in Figure 12.

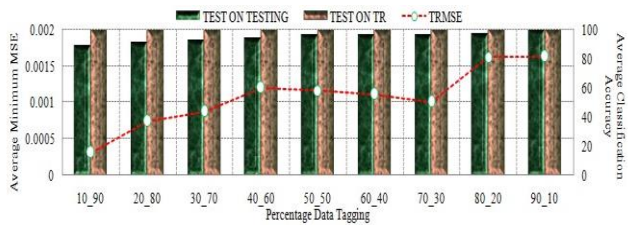


Figure 12. Variation in average classification accuracy with testing on testing and training dataset and percent data tagged for training

IV. RESULTS AND DISCUSSION

In this paper, the authors examined the results of the developed WAVELET-ANN based classifier for detection and classification of six frequently observed conditions of power system. As training is over, the learned network is enough intelligent to detect different types of disturbances efficiently. Combination of Transfer function Tanh-Axon and Step Learning Rule gives the best results. By performing Static parameter analysis, numbers of inputs are reduced from 80 to 14 (82.5%). In power quality disturbance recognition ANN based classifier works as an elegant classifier, in the sense that, ave. min. MSE of training is consistently observed as reasonably low as 0.001179 and time required per epoch per exemplar is just 0.1822 micro-sec. In addition, average classification accuracy on training as well as cross validation instances is obtained as 99.18% and 97.62%, respectively indicating a reasonable classification.

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