A Comparison of Back propagation and PSO for training RBF Neural Network for Wavelet based Detection and Classification of Power Quality Disturbances

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Abstract – This paper introduces a novel approach to detect and classify power quality disturbances in the power system using Radial Basis Function Neural Networks (RBFNN) trained by Particle Swarm Optimization (PSO).Back Propagation (BP) algorithm is the most commonly used for training, but it suffers from extensive computation and also convergence speed is relatively slow. Feature extracted through the wavelet is used for training. After training, the weight obtained is used to classify the power quality problems. For classification, 8 types of disturbance are taken in to account. The classification performance of RBFNN trained PSO algorithm is compared with BP algorithm. The simulation result using PSO possess significant improvement over BP methods in signal detection and classification.

Keywords: Power Quality, Radial basis function neural network, wavelet transformation, Back Propagation, Particle Swarm Optimization

1. Introduction

The quality of electric power is more important because one of the main problems the industries facing is the distortion in electrical supply. The disturbance such as voltage sag, swell with and without harmonics, momentary interruption, harmonic distortion, notch, flicker, spike and transients causing problems such as a malfunction, instability, short lifetimes, failure of electrical equipments and so on. Switching off large load and energization of large capacitor may cause voltage swell. Whereas the faults leading to voltage sag or momentary interruption, harmonic distortion and notching in the voltage and current are caused because of the usage of solid state switching device and nonlinear power electronically switched loads such as rectifier or inverters. Transformer energization or capacitor switching may cause transients. Flicker is caused because of the furnaces and lightning strikes may lead to spikes.

In a power system, these disturbances need to be identified in order to improve power quality (PQ). PQ event identification is difficult because it involves a wide range of disturbance categories. Therefore, the decision boundaries of disturbance features may overlap. For these reasons, the need of power quality analysis has been strongly increasing. Many techniques have been proposed in the literature to detect and classify the events envelope. Traditionally, probabilistic approach has been used for time varying signals in a power quality analysis, assuming that the power line disturbance components vary too slowly to affect the accuracy of analytical process [1-3]. Another paper has suggested a combination of spectral method with probabilistic approach, also referred as evolutionary spectrum [4].

The Discrete Fourier Transforms (DFT), which is computed via the Fast Fourier Transforms (FFT), is used to extract the features in the waveforms. However, the accuracy of the DFT algorithm is affected by the product availability in the voltage waveform. Transient characteristics of disturbances waveforms are discussed in [5], since they pertain to signal analysis. This analytic technique includes the Short-Time Fourier Transform (STFT) which briefs time–frequency information related to disturbance waveforms. However, the disturbance signal cannot be adequately described in this transform, due to fixed window size [6].

For this reason, S-Transform (ST) is often adopted as a tool for signal analysis. The superior properties of the ST are due to the fact that the modulating sinusoidal is fixed with respect to the time axis, while the localizing scalable Gaussian window dilates and translates. As a result, the phase spectrum is absolute in the sense that it always referred to the origin of the time axis, the fixed reference point. ST is found to be superior [7].However, the computational time is very large compared to Wavelet Transform (WT), which is undesirable for on-line applications. WT based approach, such as wavelet Multi-resolution analysis (MRA), has been widely applied to solve these issues [8].

Wavelet transform and multi-resolution analysis provide a short window for high frequency components and long window for low frequency components [9-11] and hence, provides an excellent time frequency resolution. This allows WT for analysis of signals with localized disturbances components and also for classifying low and high frequency power quality problems. Using the properties of WT technique and the features of the decomposed waveforms, along with ANN algorithm [12-14], it is possible to extract important information from a disturbing signal for to determine the type of disturbance that caused. The energy of the distorted signal will be partitioned at different resolution levels in different ways depending on the event available. The standard deviation can be considered as a measure of energy signal with zero mean [15-19].

The classification of seven types of PQ disturbances with self organizing learning array system considering 11 features, besides 22 families of wavelet are tested to identify the best one for a better classification. Classification of seven types of PQ events using wavelets and Probabilistic Neural Network (PNN) is given in [20]. Energy distribution at 13 decomposition levels of wavelet and time duration of each disturbance are taken as features and applied to PNN for classification. If a large number of features is considered, it may result in high memory and computational overhead. Further, eleven types of PQ events are also classified with the help of ST and PNN using only four-dimensional feature sets for training and testing. The computation time is also very large compared to WT.

Considering all these issues related to detection and classification of PQ events, a Radial Basis Function Neural Network (RBFNN) classifier based on wavelet transform trained by PSO algorithm is proposed in this paper. BP algorithm is a straightforward algorithm which is based on the steepest descent method. Backwards calculating weight does not seem to be biologically plausible. Neurons synaptic weight adjustment do not seems to work backward, and also in the design of RBFNN trained by BP algorithm a set of system variables which affect voltage most were selected as RBFNN inputs, if the range of variation is increased, the accuracy of the voltage estimation greatly suffers. Furthermore, it suffers from extensive calculation and therefore in most of the cases has a slow convergence speed. PSO can be a solution which models the cognitive as well as the social behavior of a flock of birds which are in search of food over an area [21].It improves neural network in various aspects such as learning algorithm, network connection weight and architecture .

Here, less number of features are required for effective classification of 8 types of PQ events.The RBFNN-PSO provides accurate results even with inputs found out under high noisy conditions.

The performance of RBFNN-PSO is compared with RBFNN-BP, to prove the stability and accuracy of the classification. The proposed method is tested with the inclusion of white noise in the signal. From the simulation results, it is found that RBFNN-PSO classifies he PQ event more effectively than the other well known BP algorithm.

To summarize, the paper shows the power quality problems classification using wavelet transformation and RBFNN-PSO. First the work handles with wavelet transformation and feature extraction from WT needed by the neural networks for training and for effective classification for all the 8 types. Next the paper describes the structure and results and discussion about detection and classification PQ events using RBFNN-BP and similarly for RBFNN-PSO. Finally, the performance of RBFNN-PSO is evaluated by simulation and compared with well-known RBFNN-BP.

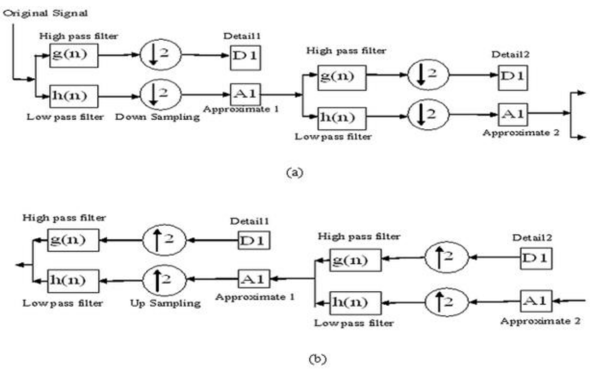
2. Wavelet Transforms

Wavelet transformation has the ability to analyze different power quality disturbances in both time and frequency domain. The wavelet transform is useful in extracting features of various power quality disturbances. Wavelet analysis deals with expansion of functions in terms of a set of basis function. However, wavelet analysis expands functions not in terms of trigonometric polynomials,but in terms of wavelets.Moreover, another important property that the wavelet possesses is perfect reconstruction, which is the process of reassembling a decomposed signal or image into its original form without loss of information.

Scaling function and wavelet function are used as building blocks to decompose and construct the signal at different resolution levels in MRA. Representation of signals at various levels of resolution is the ultimate goal of MRA. MRA consists of two filters in each level and they are low pass and high pass filters.

The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by up-sampling and down-sampling operations. Sub-sampling a signal corresponds to reducing of the sampling rate, or removing some of the samples of the signal. On the other hand, upsampling a signal corresponds to increasing the sampling rate of a signal by adding new samples to the signal. MRA decomposition and reconstruction are shown in Fig.1 (a) and (b).[22]

Fig.1 (a).Multiresolution analysis decompositionand (b)



Multiresolution analysis reconstruction

Assume a signal *x[n]*, discrete time signal is distributed in 2 level. This signal is filtered into high frequency component in level 1 by using a high pass filter *(g(n))* and low frequency components in level 2 by using a low pass filter *(h(n))*. This signal is passed through down sampling and in MRA level 2.The components in level 1 are used as initial signals. These signals are passed through high-pass filter and low-pass filter. The outputs of filter can be mathematically expressed as in equation (1) and (2) as follows.

$$y1[k] = \sum_n x[n].g[2k-n] \quad (1)$$

$$y2[k] = \sum_n x[n].h[2k-n] \quad (2)$$

Where *g(n)* is a high pass filter.
h(n) is a low-pass filter.
Where $y1[k]$ and $y2[k]$ are the outputs of the high-pass and low-pass filters, respectively [22].

3. Wavelet Based Feature Extraction

Power system comprised of various kinds of electrical disturbances such as sag, swell, momentary interruption, voltage fluctuation, harmonics etc. and they are generated using MATLAB code. The generated waveform shows the plot of amplitude of a given magnitude in the time frequency coordinate system.

*Voltage Sag***:** This problem occurs due to a fault or switching of heavy loads. The amplitude of voltage drops by 10 to 90 percent of the rated value due to the sag condition as shown in Fig.2 (b).

*Voltage Swell***:** When the normal voltage signals increases by 10 to 90 percent, it is known as voltage swell and is, shown in Fig.2(c).In this way, remaining classes are simulated as shown in Fig.2(d) – Fig.2(h) and corresponding signals are processed through the wavelet transform and represented by a set of wavelet coefficients.

$$EDi = \sum_{j=0}^{n} Dij^2 \quad (3)$$

$$EAi = \sum_{j=0}^{n} Aij^2 \quad (4)$$

Where *i*= 1,2 …….*l* is the wavelet decomposition level from level 1 to level *l*. *N* is the number of the coefficients of detail (or) approximate at each decomposition level. *EDi* is the energy of the detail on decomposition level *l* and *EAi* is the energy of the approximate at decomposition level *l*. In this way, the wavelet based feature extraction for future analysis has been constructed for the following events S1 to S8.

S1 Normal
S2 Pure sag
S3 Pure swell
S4 Momentary interruption
S5 Voltage fluctuation
S6 Harmonics
S7 Transients
S8 Combination Events

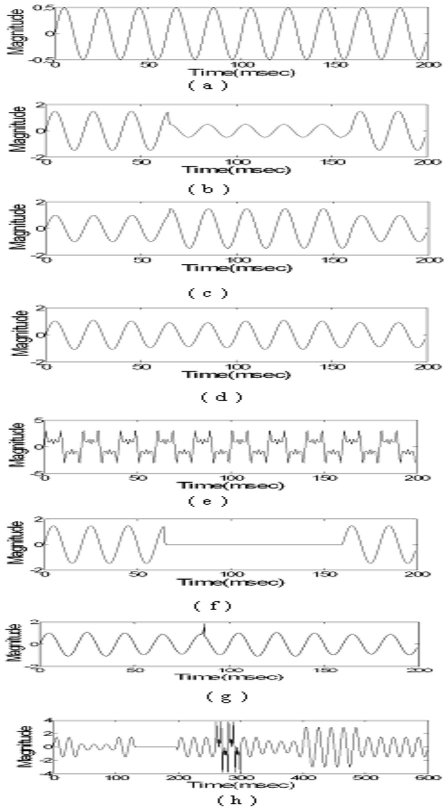


Fig. 2(a). Normal Signal (b) Pure sag (c) Pure swell (d) Momentary interruption (e) Voltage Fluctuaton (f) Harmonics (g) Transients (h) Combination of Events

4. Radial Basis Function Neural Network

Radial basis function neural network consists of a network similar to back propagation network as shown in Fig. 3 with a single hidden layer. RBFNN proves to be best for classification task from the investigation result presented in [23].Each hidden layer consists of smoothing factor σ_i and a centroids c_i. The distance between the input x_i and the centroid c_i are normally computed by the neurons. The outputs are a radial symmetrical function of the distance [24].When x_i is close to value c_i the output will be a strong one.

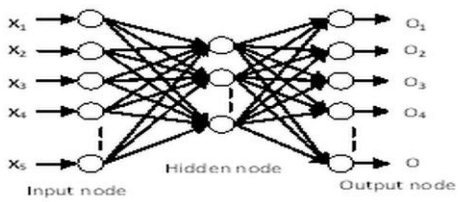


Fig. 3.Architecture of NN

The real mapping function f_m in general form

$$f_m(x) = \sum_{i=1}^{M} w_i \, k[\, (x_i - c_i\,)/\, \sigma_i] \qquad (5)$$

The function k is a radial symmetrical kernel function computed by M kernel units.
The Gaussian exponential function used in RBF is

$$f(x) = \beta \exp\left(-\sum_i [\, (x_i - c_i\,)/\, \sigma_i]^2\,\right) \qquad (6)$$

According to the training data set, centroid c_i , constant β and σ_i have to be chosen [25].

5. Results and Disscussion for Detection and Classification Using RBFNN-BP

For training any neural network backprobogation is most commonly used, in which it back- propagates its error during training. Normally neural networks train the input and a set of data of expected output for particular inputs. The sequential steps that carried out for the detection and classification is shown in Fig 4

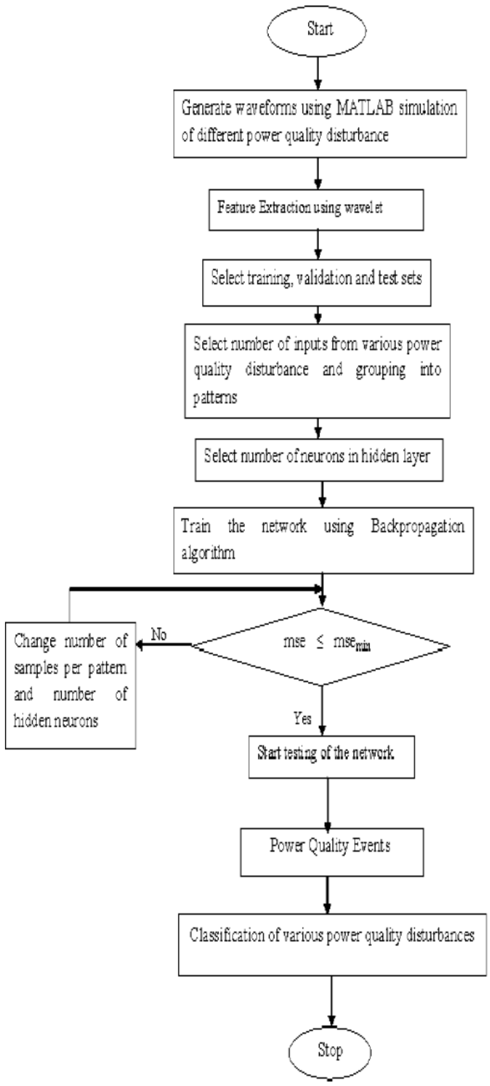


Fig. 4.Back-Propagation

The simulation of combined wavelet transformation with RBFNN-BP for classification of 8 types of power quality problems was simulated. Here, amplitude, mean, standard deviation, mean absolute deviation, median absolute deviation and energy are used as inputs to the RBFNN. Input signal for training is selected by random signal at a time. The training is set for learning rate 0.01 and target error 0.001. Each network is trained with 30 input data of each class and 100 data of each class are considered for testing. Centre and weights are updated with each and every iteration, after training the RBFNN-BP and then in this way new training input is given to the network. The randomly selected signal from 100 signals of each power quality problem is used to test RBFNN-BP. The classification result during testing is shown from Tables 1.The diagonal elements are correctly classified PQ events where as off diagonal elements represents the misclassification. The overall accuracy of classification is the ratio of correctly classified events to that of the total number of events. The overall classification accuracy is 95.87% respectively. Then the networks are trained and subsequently tested for higher number of classes with the same data.

TABLE I

Disturbance	S1	S2	S3	S4	S5	S6	S7	S8
S1	**100**	0	0	0	0	0	0	0
S2	2	**98**	0	0	0	0	0	0
S3	4	0	**93**	3	0	0	0	0
S4	0	0	0	**98**	0	2	0	0
S5	0	4	0	0	**96**	0	0	0
S6	4	0	0	0	0	**94**	0	2
S7	0	0	0	0	3	0	**96**	1
S8	0	0	0	1	2	0	5	**92**

CLASSIFICATION RESULTS OF RBFNN-BP

6. Partical Swarm Optimization

Population based optimization tool is the PSO.To get the optimal solution, every single solution 'flies' over the solution space. To check how close they are optimal is evaluated by using a fitness function [21].

Particles may have both cognitive and socialization. The neural network weight matrix is rewritten as an array to form a particle, and then initialized randomly and updated afterwards, according to the equation as (7) and (8).

$$w(t+1) = w(t) + \Delta w(t+1) \quad (7)$$

$$\Delta w(t+1) = .\Delta w(t) + c_1.rand(\,).[pBest\ (t) - w(t)] + c_2.rand(\,).[gBest\ (t) - w(t)] \quad (8)$$

Where w, c_1, c_2 is inertia, cognitive and social acceleration constant respectively [26].

pBest is the best solution that the particle has achieved and indicates the tendency to replicate their corresponding past behaviors. *gBest* is the best solution that has achieved so far by the specific particle in the whole population, which indicates the tendency to follow the success of others by the particles . Another important parameter is the maximum velocity V_{max} , associated with PSO,which mainly determines the resolution with which the search space is searched. There may be chances to fly past better solution by the particle if the value is very large and get trapped in the local optima if the value is small.

7. Results and Disscussion for Detection and Classification Using RBFNN-PSO

The PSO algorithm is different than any other technique, rather than training one network PSO trains a network of networks. It initializes all weights to random values and starts training each other, on each pass, PSO compare networks fitness. Each network contains position and velocity. The position is related to weight and the velocity refers to updating of neural networks weights. Getting the best set of weight is the main function of PSO in RBFNN. In RBFNN implementation, the fitness value corresponds to a forward propagation and position vector corresponds to the weight vector. The best neighbor and global best are used to guide the particle new solution. Input variables are amplitude, mean, standard deviation, mean absolute deviation, median absolute deviation and energy. To speed up the training, the variables are normalized. The function of PSO in RBFNN is to get the best set of weight. 80% of the generated inputs were used for training and remaining 20% were used for testing. For RBFNN-PSO with different initial weight, a population of neural networks was constructed and sum of square error in each iteration over the training data set were calculated and compared to find the best network in the neighborhood .If minimum error required is achieved by the network means this weight is recorded for to use it for testing, other wise again the algorithm is applied to get the best weight and updating of weight i.e position and velocity vector for each network. After training the test signals are applied to evaluate the performance of the trained RBFNN-PSO. In this way the randomly selected signals from 100 signals of each power quality problem is used to test RBFNN-PSO. The classification result during testing is shown in Table 2, in these diagonal elements are correctly classified PQ events, and where as off diagonal elements represent the misclassification.

Disturbance	S1	S2	S3	S4	S5	S6	S7	S8
S1	**100**	0	0	0	0	0	0	0
S2	2	**98**	0	0	0	0	0	0
S3	2	0	**96**	2	0	0	0	0
S4	0	0	1	**98**	0	1	0	0
S5	0	0	0	0	**100**	0	0	0
S6	0	2	0	0	0	**98**	0	0
S7	0	0	0	0	0	0	**100**	0
S8	0	0	1	0	3	0	0	**96**

TABLE II
CLASSIFICATION RESULTS OF RBFNN-PSO

The overall accuracy of classification is the ratio of correctly classified events to that the of total number of events. The overall classification accuracy is 98.25 %.

It is identified that RBFNN gives the best classification results in this case.In training RBFNN-PSO, the inputs for training are noise free. However, the signals in the real system will always have noise. In order to test the robustness of RBFNN-PSO, the white noise, which has random normal distribution, is added to normal signal to test the performance of RBFNN-PSO under noisy environment. The test results are depicted in Table 3. As seen from the simulation results, wavelet transformation with RBFNN-PSO is able to detect and classify the power quality problems correctly.

TABLE III
SIMULATION RESULTS OF CLASSIFICATION THE POWER QUALITY PEOBLEMS WITH NOISE

Disturbance	S1	S2	S3	S4	S5	S6	S7	S8
S1	**100**	0	0	0	0	0	0	0
S2	0	**95**	2	0	0	3	0	0
S3	0	0	**97**	3	0	0	0	0
S4	0	2	0	**98**	0	0	0	0
S5	2	1	0	2	**94**	0	1	0
S6	0	0	0	0	0	**98**	0	2
S7	1	0	0	0	0	0	**98**	1
S8	0	0	2	0	4	0	0	**94**

8. Conclusion

In this paper, the application of wavelet transforms combined with RBFNN and PSO technique, to detect and classify various PQ disturbances is presented. A numerical simulation is conducted to exhibit the properties of WT-based MRA. The feature extracted by wavelet is used as inputs to RBFNN-BP detection and classification. The classification accuracy of the RBFNN network is improved, just by rewriting the weights and updating of weights with cognitive as well as the social behavior of particles along with a fitness value by PSO algorithm. The performance of RBFNN-PSO is compared with RBFNN-BP. The proposed method stands as an evident that it can be implemented in any online application.

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