RBFNN Based Power Quality Issues Detection and Classification using Wavelet-PSO

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Abstract: This paper introduces a new 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 frequently used for training, but it suffers from extensive computation and also convergence speed is relatively slow. Feature mined through the wavelet is used for training. After training, the weight obtained is used to classify the power quality issues. For classification, 8 types of disturbance are taken in to explanation. The classification performance of RBFNN trained PSO algorithm is matched with BP algorithm. The simulation result using PSO have 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

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1. Introduction

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

In a power system, these issues need to be identified in order to improve power quality (PQ). PQ event identification is tough because it involves a wide range of disturbance categories. Therefore, the decision boundaries of event features may overlap. For these reasons, the need of power quality analysis has been strongly growing. Many techniques have been proposed in the literature to identify and classify the events envelope. Conventionally, probabilistic approach has been used for time varying signals in a power quality analysis, assuming that the power line disturbance apparatuses vary too slowly to affect the accuracy of logical 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 matters 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 projected in this work. BP algorithm is a straight forward algorithm which is constructed on the steepest descent method. Backwards calculating weight does not seem to be biologically credible. Neurons synaptic weight modification 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 utmost were selected as RBFNN inputs, if the range of variation is increased, the precision of the voltage estimation greatly suffers. Furthermore, it suffers from extensive calculation and therefore in most of the cases has a very 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 range [21].It advances neural network in various aspects such as learning algorithm, network connection weight and construction.

Here, less number of features is required for actual classification of 8 types of PQ events.The RBFNN-PSO delivers accurate results even with inputs with under high noisy conditions.

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

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

2. Wavelet Transforms

Wavelet transformation has the skill to analyze different power quality disturbances in both time and frequency domain. The wavelet transform is useful in mining features of various power quality disturbances. Wavelet analysis handles with expansion of functions in terms of a set of basis function. However, wavelet analysis develops functions not in terms of trigonometric polynomials, but in terms of wavelets. Moreover, another important property that the wavelet has is perfect reconstruction, which is the process of reassembling a decomposed signal into its original form without loss of information.[1]

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

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

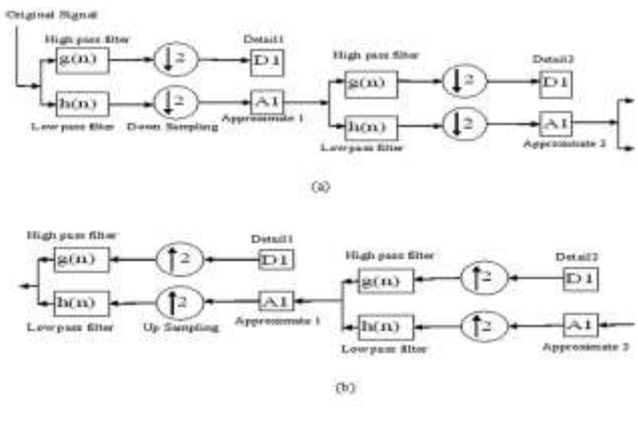

Fig.1 (a).Multi-resolution analysis decomposition (b) reconstruction

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

$$y1[k] = \sum_n x[n].g[2k-n] \quad (1)$$
$$y2[k] = \sum_n x[n].h[2k-n] \quad (2)$$

g(n) is a high pass filter.
h(n) is a low-pass filter.
$y1[k]$ and $y2[k]$ are the outputs of the high- pass and low-pass filters, respectively. [2]

3. Wavelet Based Feature Extraction

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

Voltage Sag: It 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 situation as shown in Fig.2 (b).

Voltage Swell: When the normal operating 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 generated as shown in Fig.2(d) – Fig.2(h) and simulated signals are handled through the wavelet transform and represented by a set of coefficients.

$$EDi = \sum_{j=0}^{n} Dij^2 \quad (3)$$
$$EAi = \sum_{j=0}^{n} Aij^2 \quad (4)$$

i= 1,2 …….*l* is the wavelet decomposition level from level 1 to level *l*. *N* is the coefficients of detail (or) approximate at each decomposition level. ED_i is the energy that is information level of the detail decomposition for a level *l* and EA_i is the energy of the approximate at decomposition level *l*. In this way, the wavelet based feature extraction for future analysis has constructed for the following events from S1 to S8 [2].

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

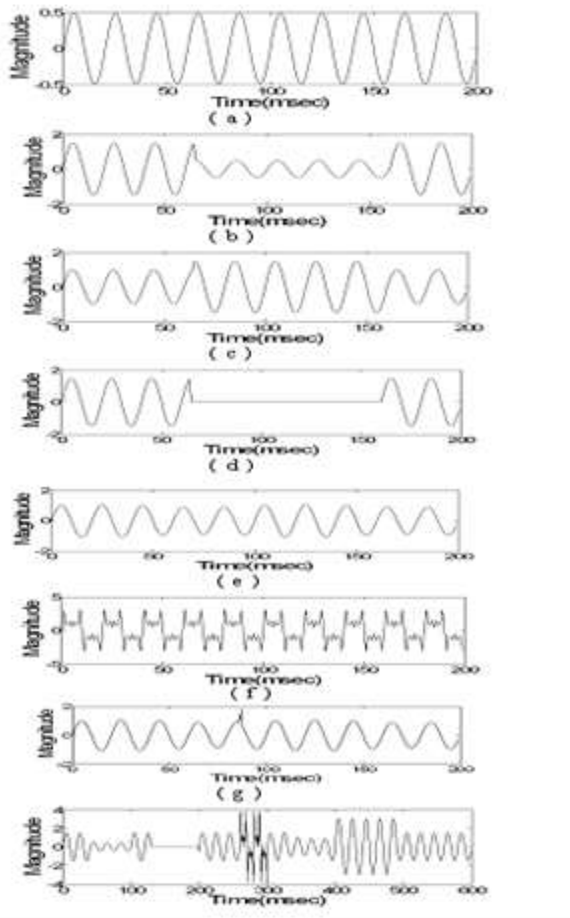

Fig. 2 Various Electrical Signals (a). Normal Signal (b) Pure sag (c) Pure swell (d) Momentary interruption (e) Voltage Fluctuaton (f) Harmonics (g) Transients (h) Combination of Events

4. Radial Basis Function Neural Network

Radial basis function neural network contains network similar to back propagation network as shown in Fig. 3 with a hidden layer. RBFNN proves to be best for classification work from result presented in [22].Each hidden layer contains of smoothing factor σ_i and a centroids c_i. The distance between the input x_i and the centroid c_i are normally calculated by the neurons. The outputs for this particular networks are radial symmetrical function of the distance [23].When x_i is nearer to value c_i the output will be a strong one [1].

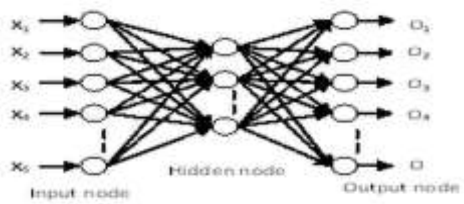

Fig. 3.Architecture of neural network

The 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 calculated by M kernel units.
The Gaussian exponential function used in this work 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 appropriately.

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

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

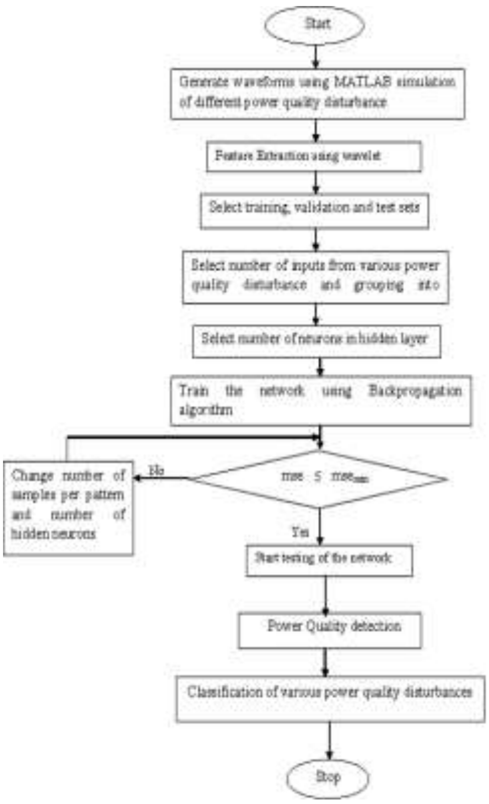

Fig. 4.Back-Propagation Algorithm

The simulation of wavelet transformation with RBFNN-BP for classification of 8 types of power quality problems was simulated using MATLAB. Here, amplitude, mean, standard deviation, mean absolute deviation, median absolute deviation and energy are the inputs to the RBFNN. Input signal for training is selected by randomly at a time. The training is carried by setting 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 taken in to account for testing. Centre and weights are updated during every iteration after training the RBFNN-BP, in this way new training input is given to the network. The randomly selected signal from 100 signals of each power quality problem for various orientations is used to test RBFNN-BP. The classification result during testing is shown in Tables 1.The diagonal elements are correctly classified events where as off diagonal elements signifies the misclassification. The overall accuracy of classification is the ratio of correctly classified issues to that of the total number of issues. The overall classification accuracy is 95.87% respectively. Then the networks are trained and subsequently tested for higher counts of classes with the same data.

TABLE I
CLASSIFDICATION RESULTS OF RBFNN-BP

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**

6. Partical Swarm Optimization

This technique is one of the population based optimization tool. To get the optimal solution, every single solution ‘flies’ over the space . To check how close they are, optimal is evaluated by using a fitness value [21].

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

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

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

w, c_1, c_2 is inertia, cognitive and social acceleration constant respectively [24].

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

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

The PSO algorithm is somewhat different than any other technique, rather than training a network PSO trains a network of networks. It initializes all weights to random values and starts training each other, on each pass, PSO checks and compares networks fitness. Each network comprises position and velocity. The position refers 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 application, the fitness value relates to a forward propagation and position vector relates to the weight vector. The best and global best are used to guide the particle new solution. Inputs are amplitude, mean, standard deviation, mean absolute deviation, median absolute deviation and energy. To speed up the training process, the variables are normalized. The purpose of having PSO in RBFNN is to get the best set of weight. 80% of the generated inputs were used for training and 20% were used for testing purpose. For RBFNN-PSO with different initial weight, a population of neural networks was created and sum of square error in each iteration were calculated and compared to find the best network in the neighborhood .If minimum error required is attained, this weight is logged 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 all the networks. After training the test signals are applied to estimate the performance of the trained RBFNN-PSO. In this way the randomly selected signals from 100 signals of each issue is used to test RBFNN-PSO. The classification result during testing is shown in Table 2, in these diagonal elements are correctly classified PQ issues, and where as off diagonal elements are misclassification.

TABLE II
CLASSIFDICATION RESULTS OF RBFNN-PSO

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**

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

It is identified that RBFNN provides the best classification results in this case.In training RBFNN-PSO, the inputs for training are mostly noise free. However, the signals in the real system will always have some amount of noise. In order to test the potential and 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 shown in Table 3. As seen from the simulation results, RBFNN-PSO is able to detect and classify the power quality problems correctly with more accuracy rate.

TABLE III
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	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**

8. Conclusion

In this paper, the application of wavelet transforms combined with RBFNN and PSO, to detect and classify

PQ disturbances is presented. Simulation is conducted to exhibit the properties of WT-based MRA. The feature extracted by wavelet is used as inputs to RBFNN-BP. The classification accuracy of the RBFNN network is improved, just by updating the 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 initially simulated results given by RBFNN-BP. The proposed method stands as an evident that it can be used in any online application.

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