

Comparison Of Power Quality Disturbances Classification Based On Neural Network

Nway Nway Kyaw Win, Theingi Zin, Hla Myo Tun

Abstract: Power quality disturbances (PQDs) result serious problems in the reliability, safety and economy of power system network. In order to improve electric power quality events, the detection and classification of PQDs must be made type of transient fault. Software analysis of wavelet transform with multiresolution analysis (MRA) algorithm and feed forward neural network (probabilistic and multilayer feed forward neural network) based methodology for automatic classification of eight types of PQ signals (flicker, harmonics, sag, swell, impulse, fluctuation, notch and oscillatory) will be presented. The wavelet family, Db4 is chosen in this system to calculate the values of detailed energy distributions as input features for classification because it can perform well in detecting and localizing various types of PQ disturbances. This technique classifies the types of PQDs problem severents. The classifiers classify and identify the disturbance type according to the energy distribution. The results show that the PNN can analyze different power disturbance types efficiently. Therefore, it can be seen that PNN has better classification accuracy than MLFF.

Keywords: Power quality disturbances, wavelet transform, energy distribution, probabilistic neural network, multilayer feed forward neural network

I. INTRODUCTION

Power quality is defined as any deviation in power (voltage, current, or frequency) that impacts the normal operation of electrical equipments. Poor power quality may result many electrical faults for the affected loads such as malfunctions, instabilities, short life-time and so on. Power Quality (PQ) events such as sag, swell, transient, harmonics, notch, fluctuation and flicker are the most common types of disturbances that occurring a power line. Any disturbances can adversely affect the user's equipment .Therefore, it is necessary to analyze efficiently and to understand deeply these disturbances. The features extracted by signal processing techniques are used as input to the PQ classification system. In power quality disturbances feature extraction techniques include frequency transform such as Fourier Transform (FT) and the Short Time Fourier transform (STFT), Wavelet Transform (WT) and S-Transform(S-transform). Wavelet transform (WT) is localized in time and frequency yielding wavelet coefficients at different scales. Energy distributions are calculated to use input features in classification stage with the help of mother wavelet which is Daubechies4 at 10 decomposition level. By investigating detection or classification PQ events, power problems will be not only protected but also reduced power transmission faults. Although there are various PQ signals in real time, eight PQ signals like flicker, harmonic , sag, swell, impulse ,fluctuation, notch and oscillatory will be created as input signal in this system. The detail coefficients obtained from wavelet transform are given to the classifiers such as probabilistic neural network and multilayer feed forward neural network. In probabilistic neural network, there is no need to set hidden layer, hidden neuron, and activation function and iteration time. Whereas, multilayer feed

forward neural network is considered to these facts. In this system, PQ events are needed to classify with the aid of neural network The quality of electric power has been become an essential issue because it is widely spread use of many application areas such as hospital, university, home appliances , industry, etc which are more aware and sensitive to power quality.

II. THE OVERALL BLOCK DIAGRAM OF PQ DISTURBANCES CLASSIFICATION

The overall block diagram of PQ disturbances Classification is illustrated in Figure 1. There are two stages in this figure .They are features extraction stage and classification stage. Firstly, the input PQ disturbance signal such as flicker, harmonics, sag, swell, impulse, fluctuation, notch and oscillatory are generated using their mathematical equations and parameters with the help of Mat lab programming .And then, the generated PQ signals are decomposed by using wavelet transform. The wavelet transform can be used for decomposing and denoising the signal. In this paper, wavelet is only applied for decomposition of PQ signals. These signals are divided into 10 decomposition levels. After decomposition, approximation and detail coefficients of the signal are provided to apply as feature extraction. The wavelet family, Db4 is chosen in this system to calculate the values of detailed energy distributions as input features for classification because it can perform well indetecting and localizing various types of PQ disturbances. In classification stage, the energy distribution features from getting decomposition level of each signal are fed as inputs to classify the types of PQ signals such as flicker , harmonics ,sag , swell ,impulse, fluctuation ,notch and oscillatory by using various types of neural network such as probabilistic neural network, multilayer feed forward , radial basic function and so on. In order to achieve the best one, classification accuracy of PQ disturbance can be compared with each other by using various types of neural network.

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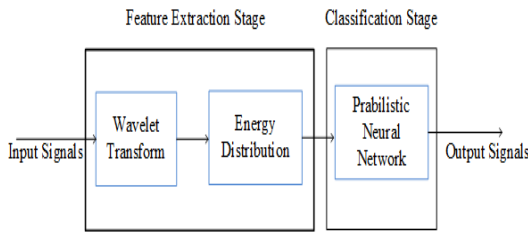


Figure 1. Overall Block diagram of PQ disturbances Classification

III. POWER QUALITY DISTURBANCE CLASSIFICATION

Feature extraction stage is needed to provide as input in neural network. Probabilistic neural network and multilayer feed forward neural network are used to classify the power quality disturbances. The computed energy distribution values for input features are used to construct the training and testing data to model the PNN and MLFF program with the help of Matlab.

A. Wavelet Transform and Multi-Resolution Analysis(MRA)

Wavelet transform is very useful tool for power quality disturbances detection and classification. The wavelet transform has the capability to analyze both time and frequency domains, hence, give the time frequency representation of signal like the Short Time Fourier Transform(STFT).Unlike the STFT which uses a fixed window function, the WT makes use of a varied time frequency window whose length depends on the frequency analyzed using long windows at low frequencies and short windows at high frequencies. Therefore, the WT at low frequency provides accurate frequency resolution and poor time location, and at high frequency, WT gives accurate time location and bad frequency resolution. Therefore, it is used as a feature extraction tool to identify power quality disturbances. In multi resolution analysis (MRA), wavelet functions and scaling functions are used as building blocks to decompose and construct the signal at different resolution levels. The wavelet function will generate the detail version of the decomposed signal which constitutes the high pass digital filter and the scaling function will generate the approximated version of the decomposed signal which constitutes low pass digital filter.

B. Signal Generation and Energy Distribution

PQ analysis can be made in real time and off-line condition. In this system, PQ signal disturbances are used to classify in off-line condition. In feature extraction stage, the PQ disturbance signals have been generated by using their signal generation model and parameters based on Matlab. The coefficients of the detailed energy distributions are calculated by using wavelet transform at 10 decomposition levels... The energy distribution features from getting decomposition level of each signal are fed as inputs to classify the types of PQ signals. Each disturbance has a unique detailed energy distribution. The energy distribution of a distorted signal can be used as a

discriminatory feature for classification. In this paper, the detailed energy distribution of a distorted signal can be fed as input for classification stage. The energy of a distorted signal at a resolution level j is given by equation (1)

$$E_j = \sum_{i=1}^{N_m} (d_j(i))^2 \tag{1}$$

Where N_m is the number of available wavelets coefficients at the resolution level j , d_j is the detail coefficient at the resolution level j .

C. Probabilistic Neural Network (PNN)

Probabilistic neural networks can be used for classification problems. PNN is a feed forward Neural Network and it is supervised learning. Four Layer Architecture consists of: input layer, hidden layer /Pattern layer, summation layer and output Layer. The input layer unit does not perform any computation and simply distributes the input to the neurons in the pattern layer. On receiving a pattern from the input layer, the neuron of the pattern layer computes its output as the probability density function (pdf) for a single sample. Probability density function(pdf) can be calculated by equation (2)

$$f_k(X) = \frac{1}{(2\pi)^{\frac{p}{2}} \cdot \sigma^p} e^{-\frac{\|X-X_k\|^2}{2\sigma^2}} \tag{2}$$

Where X is unknown input vector, X_k is k_{th} sample input vector is the smoothing parameter and p is the dimension of the input vector. The neuron of the summation layer computes its output as the pdf for a single population or pattern. The summation layer of PNN is given by equation (3)

$$g_i(X) = \frac{1}{(2\pi)^{\frac{p}{2}} \cdot \sigma^p} \frac{1}{n_i} \sum_{k=1}^{n_i} e^{-\frac{\|X-X_k\|^2}{2\sigma^2}} \tag{3}$$

Where n_i is the total number of samples in the i^{th} population. Finally, the output layer picks the maximum of these probabilities, and produces 1 for that class and 0 for the other classes. Figure 2 shows architecture of probabilistic neural network and equation (4) describes to compute the output layer of network.

$$C(X) = \arg \max\{g_i(X)\} \quad 1, 2, \dots, m \tag{4}$$

where m is the total number of classes in the training samples.

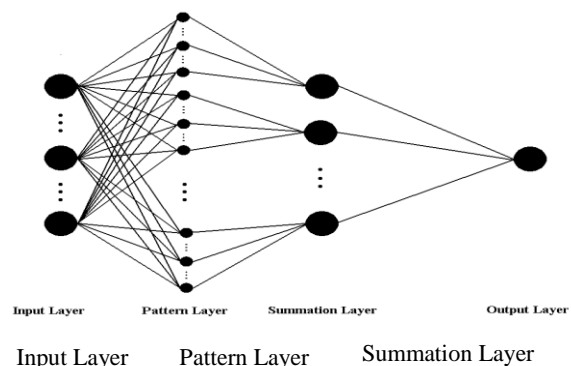


Figure 2: Architecture of PNN

D. Multilayer Feed Forward Neural Network (MLFF)

The MLFF structure generally consists of three layers. They are an input layer with neurons representing input variables to the problems, one or more hidden layers containing neurons to help to capture the nonlinearity in the data and an output layer with neurons representing the dependent variables. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The network is trained by the back propagation learning rule. The most commonly used functions are log-sigmoid, tan-sigmoid and linear transfer functions. Figure 3 shows the general structure of multilayer feed forward neural network. The goal of the training process is to find the set of weight values that will cause the output from the neural network to match the actual target values as closely as possible. There are several issues involved in designing and training a multilayer perceptron network:

- Selecting how many hidden layers to use in the network.
- Deciding how many neurons to use in each hidden layer.
- Finding a globally optimal solution that avoids local minima.
- Converging to an optimal solution in a reasonable period of time.

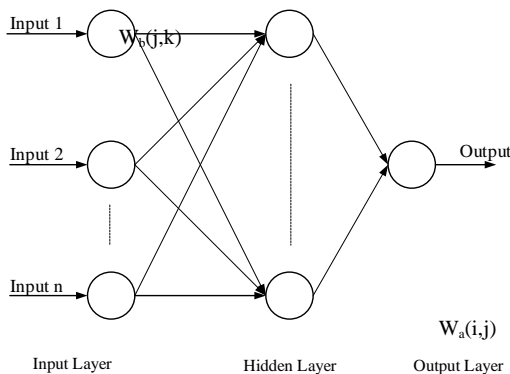


Figure 3. General structure of Multilayer Feed Forward Neural Network

IV. SOFTWARE IMPLEMENTATION

Although there are various kinds of neural network, probabilistic neural network and multilayer feed forward neural network are applied in power quality disturbances classification stage by using Matlab.

A. Probabilistic Neural Network Classification

The flowchart of probabilistic neural network classification is shown in Figure 4. The energy distribution values of PQ signals are entered as inputs in PNN. Target outputs are set and network model are created to train data. And then, this network is simulated on training data. While testing the trained data, testing feature vector is fed into the network for only forward pass through the network and the classification outputs are produced as desired outputs

such as flicker, harmonic, sag ,swell, impulse ,fluctuation, notch and oscillatory signals.

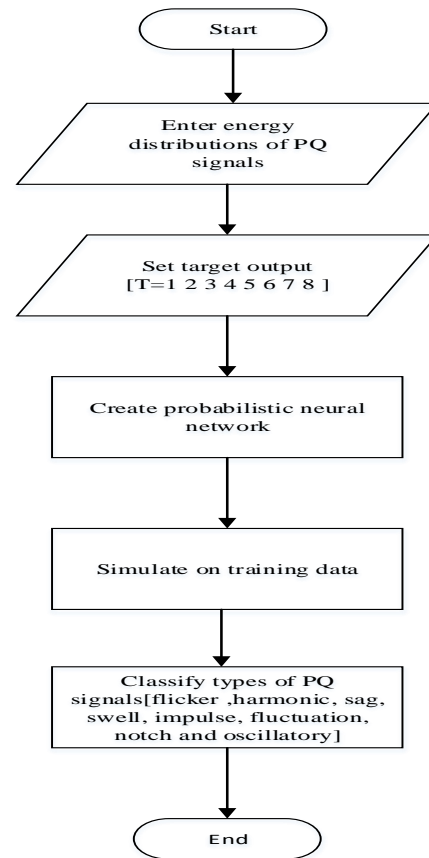


Figure 4. Flowchart of probabilistic neural network classification

The energy distribution of PQ signals such as flicker, harmonic, sag, swell, impulse, fluctuation, notch and oscillatory have been generated according to the feature extraction stage by using Matlab. The values of calculated energy distribution of power quality disturbances are shown in Table I. The detailed energy distribution of PQ signals are applied as inputs in probabilistic neural network and multilayer feed forward neural network in this system because these networks are classified the types of disturbances.

Table I: Detailed energy distributions of power quality disturbances

Signal Types	Features of distorted signals									
	E D1	E D2	E D3	E D4	E D5	ED 6	E D7	E D8	E D9	ED 10
Flicker	0.0000	0.0000	0.0000	0.0006	0.0040	0.0080	5.5799	74.3199	18.324	0.2681
Harmon	0.04	0.03	0.03	1.62	0.12	0.168	0.38	1.58	1.81	3.421

ics	95	5 2 2	3 4 0	52	51	2	15	95	90	1
Sag	0.0008	0.0129	0.0160	5.4321	21.255	0.1821	0.1240	0.2371	0.5427	1.2341
Swell	0.0005	0.0092	0.0087	9.2872	36.2710	0.1071	0.2445	0.1369	0.3095	0.8317
Impulse	0.4613	0.2757	0.2058	4.9536	24.2286	0.1077	0.2616	0.2541	1.2148	2.111
Fluctuation	0.0013	0.0326	0.0513	2.2711	0.0787	0.1774	0.3259	1.2475	1.5938	2.9737
Notch	0.2040	0.1524	0.0726	5.9591	23.5947	0.1111	0.1921	0.3256	1.46	3.99
Oscillatory	0.0489	0.1643	0.1719	5.0803	24.1943	0.0896	0.2053	0.2581	1.2670	2.2875

Table II shows eight output vectors represented for eight different power quality signals. This output target vector can be used by neural network during training stage. Network will compare these desired outputs with its actual results and hence calculate errors and adapt its weights to learn the patterns.

Table II: Output Target Vector for PQ disturbances

Power quality Disturbances	Output Target Vector
Flicker	[1 0 0 0 0 0 0]
Harmonic	[0 1 0 0 0 0 0]
Sag	[0 0 1 0 0 0 0]
Swell	[0 0 0 1 0 0 0]
Impulse	[0 0 0 0 1 0 0]
Fluctuation	[0 0 0 0 0 1 0]
Notch	[0 0 0 0 0 0 1]
Oscillatory	[0 0 0 0 0 0 1]

The most important part of the classification of power quality disturbance using neural networks is the training of the neural network. The structure of the PNN network is as shown in Figure 5. It contains two layers called radial basis layer and competitive layer. Features from the wavelet transform analysis are taken as inputs to the PNN and the outputs are binary values 0's and 1's. Neural network

Learning carried out with the speed constant of 0.1. Matlab (newpnn) function is used to design the network.

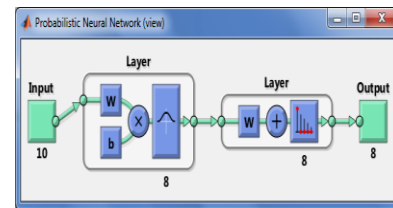


Figure 5. Structure of probabilistic neural network

B. Multilayer Feed Forward Neural Network Classification

The flowchart of multilayer feed forward neural network classification is illustrated in Figure 6. The energy values of PQ signals are entered as inputs in MLFF. Target outputs are set and then network model are designed to train data. And then, this network is simulated on training data. After the trained data is tested in the MLFF, the classified outputs are produced as desired outputs such as flicker, harmonic, sag, swell, impulse, fluctuation, notch and oscillatory signals.

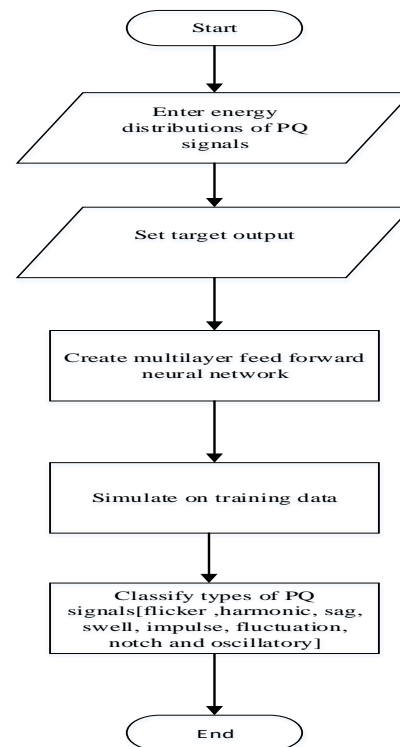


Figure 6. Flowchart of Multilayer Feed Forward Neural Network classification

Eight PQ signals are fed as inputs in the multilayer feed forward neural network. In this network, two hidden layers reused to classify the disturbance patterns. Hidden layer 1 with eight neurons and hidden layer 2 with ten neurons are applied. Performance is measured according to mean square error. Maximum epochs are set to 5000. Matlab (feedforwardnet) function is used to design the network.

Figure 7 shows the structure of multilayer feed forward neural network.

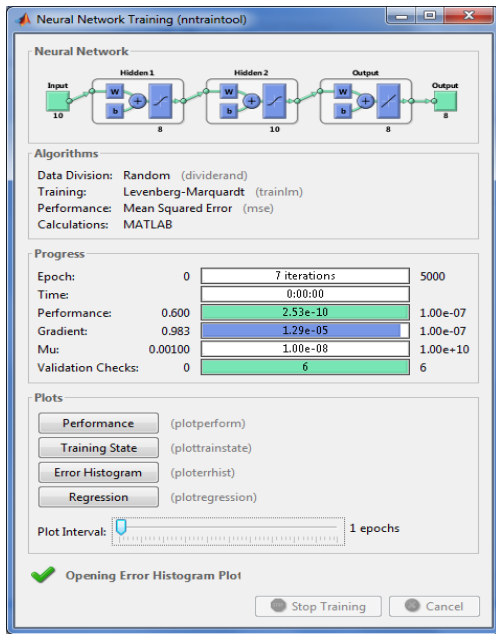
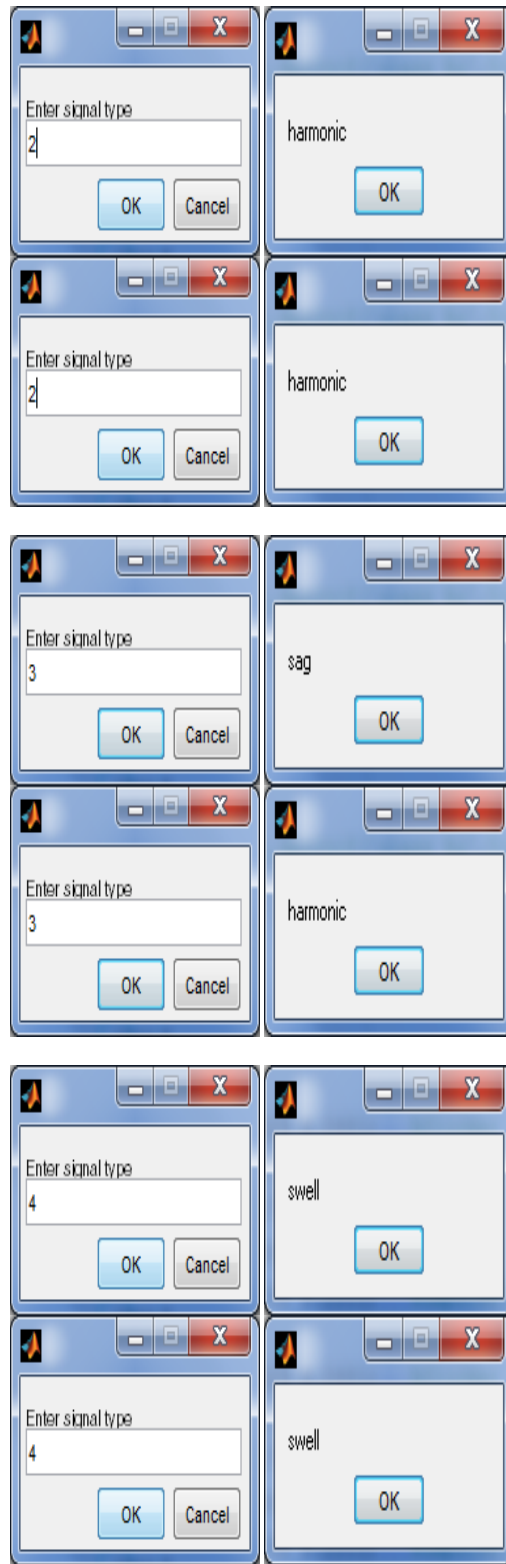


Figure 7. Structure of multilayer feed forward neural network.

V. SIMULATION RESULTS

The values of energy distribution of power quality disturbances are trained by applying PNN and MLFF. The comparison of power quality disturbances classification accuracy by using two neural networks such as PNN and MLFF is shown in Figure8 and Figure 9. According to these results, all types of PQ signals such as flicker, harmonic, sag ,swell, impulse, fluctuation, notch and oscillatory can be correctly classified by using PNN. The remaining six signals except sag and oscillatory signals can be classified by using MLFF. Therefore, it can be said that probabilistic neural network has better classification accuracy than multilayer feed forward neural network.



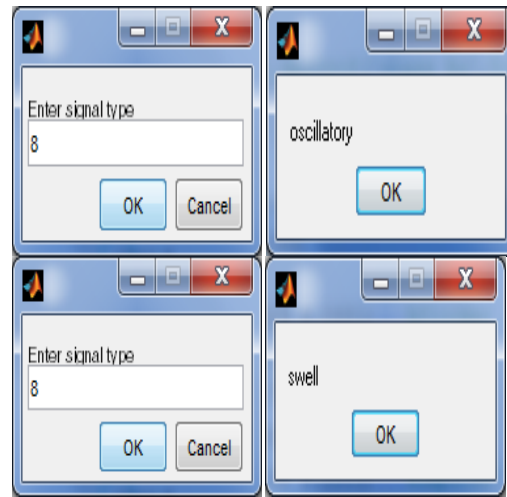
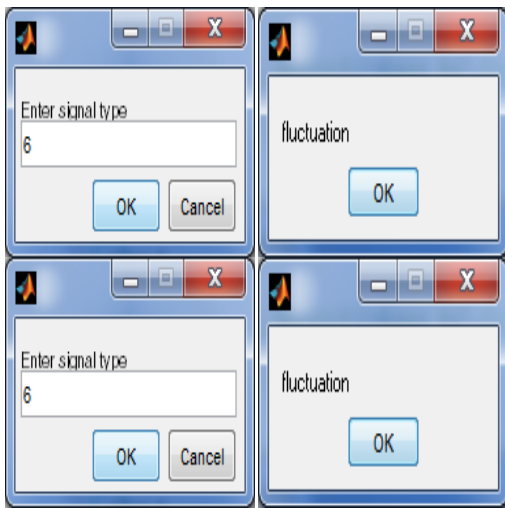
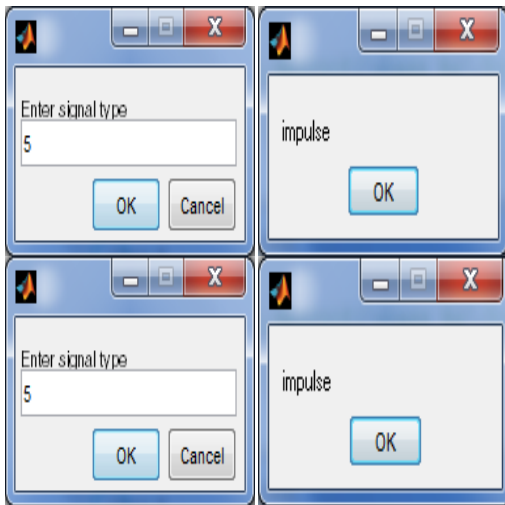


Figure 8. The classified types of PQ signals with PNN
Figure 9. The classified types of PQ signals with MLFF

VI. DISCUSSIONS AND CONCLUSION

In this system, the power quality disturbances are generated by using their equations and parameters with the aid of Matlab programming. The created power quality disturbance signals are decomposed based on wavelet transform. The wavelet transform can be applied to decompose and denoise the signals. The wavelet transform can be provided as an essential tool in the detection and classification of power quality disturbances. The selection of mother wavelet plays a vital role for decomposition of PQ signals in accurate classification and detection of disturbances. The coefficients of energy distribution do not change too much when the white Gaussian noise is added to power quality disturbance signals. In classification stage, the calculated energy distributions of PQ signals have been applied as input features in probabilistic neural network and multilayer feed forward neural network to analyze the types of disturbance signal. Although PNN model identifies the eight different types of disturbance signals including flicker, harmonic, sag, swell, impulse, fluctuation, notch and oscillatory signals with high accuracy, MLFF model cannot classify two signal types such as sag and oscillatory signals in this system. Training process for PNN is faster than other neural network (NN). As the size of representative training set increases, PNN can converge to an optimal classifier. There are no local minima issues in case of PNN. Without extensive retraining, training samples can be added or removed. The performance of network can be degraded because the values of hidden neuron and layer are assigned again and again. The classification accuracy also proves PNN as more suitable classifier for this application.

ACKNOWLEDGMENTS

The author would like to thank to Dr. Hla Myo Tun, Associate Professor and Head of the Department of Electronic Engineering, Mandalay Technological University for his help. And thanks to all teachers from Department of Electronic Engineering, Mandalay Technological University for their guidance, support and encouragement.

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