Detection of Power Quality Disturbances Based on Adaptive Neural Net and Shannon Entropy Method

D. Kavitha, P. Renuga and M. Seetha Lakshmi

Abstract Detection of power quality (PQ) events is a vital task for the power system monitoring and control. This paper presents a new scheme for the revealing of PQ disturbances using adaptive neural net (ANN) and information theory which employs neural net as a harmonics extracting unit and the difference entropy as a feature extracting unit. Simulations on six signals, such as ideal sine wave, interruption, voltage sag, voltage swell, impulse, and oscillation transient, are done with and without the presence of harmonics and the begin and end instants of disturbances are accurately tracked. The robust nature of the algorithm allows accurate estimation in the presence of noises about 10 db and the results of detection show that the proposed method has good compliance on determination of attributes of the signals.

Keywords Neural network · Difference entropy · Power quality · Detection · Harmonics

1 Introduction

Power quality (PQ) has become a momentous problem for both utilities and customers, for its adverse effects on equipments. Electric loads have become more vulnerable to power quality. Load equipments with microprocessor-based controls and power electronics devices even though worsen the PQ are more sensitive to power variations. They may suffer failure, malfunction, or hardware damage during PQ

D. Kavitha (✉) · P. Renuga · M.S. Lakshmi
Department of Electrical and Electronics Engineering, Thiagarajar College of Engineering, Madurai, Tamilnadu, India
e-mail: dkavitha@tce.edu

P. Renuga
e-mail: preee@tce.edu

M.S. Lakshmi
e-mail: mseetha@tce.edu

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events [1, 2]. When characterizing system disturbances, it is sufficient to monitor only the voltage signals. The process of converting raw measurement data into suitable PQ detection data involves data selection, information extraction, and assimilation and report presentation. These steps require advanced technology. Hence, the analysis of PQ disturbances, especially detection and location, needs to be attaching importance to. Nowadays, the scholars have carried through abundant researches on PQ detection and location, using wavelet transform [3], short-time Fourier transform, HHT transform [4], and mathematical morphology [5], et al., and have gained plentiful productions. Practically, the PQ signals are often captured with noise; therefore, the effective methods able to process such signals are indispensable. In the previous similar works [1–5], the ideal sine wave and PQ disturbances such as interruption, voltage sag, voltage swell, impulse, and oscillations transients are analyzed using different methods including Shannon entropy and the starting and ending instants of the disturbances are determined. The drawback in those works is that the authors have assumed a pure sinusoidal condition which cannot be a practical one.

Adaptive neural net (ANN) is able to handle the signals with noise and can extract the harmonics from fundamental effectively [6–8]. Entropy which can open out the developing direction of the things and measure the uncertainty and disorder of material systems has widely applied in power system [9, 10]. This paper presents a new simple PQ detection method on basis of adaptive neural network and difference entropy. The adaptive neural network has been applied in the area of PQ for the estimation of harmonics, since the network convergence is fast and the results are accurate. In this paper, a combined method using ANN and Shannon entropy is used which employs neural net as a harmonics extracting unit and the difference entropy as a feature extracting unit. The organization of the paper is as follows: In Sect. 2, the basic theories and proposed methodology including ANN and Shannon entropy are explained. Next, Sect. 3 describes the results and discussions on proposed detection method. Conclusions are finally shown in Sect. 4.

2 Proposed Methodology

a. Adaptive neural networks

In this paper, ANN is implemented to eradicate the monitoring problems occur due to the presence of harmonics. Neural networks have self-adapting and super-fast computing features that make them well suited to handle nonlinearities, uncertainties, and parameter variations that can occur in the system. The error minimization between actual and estimated signals is actually done. The general form of a harmonic signal is given by Eq. 1,

$$f(t) = \sum_{k=1}^{N} A_k \sin(\omega_k t + \varphi_k) \tag{1}$$

where A_k is the amplitude, and φ_k is the phase angle of the *k*th harmonic signal. N is the total harmonics to be estimated. ω_k is the *k*th harmonic frequency. The Eq. 1 can be rewritten as Eq. 2 to model the adaptive neurons effectively.

$$f(t) = \sum_{n=1}^{N} [Xn \cos(n\omega t) + Yn \sin(n\omega t)] \tag{2}$$

$$X_n = A_n \sin \varphi_n \tag{3}$$

$$Y_n = A_n \cos \varphi_n \tag{4}$$

where X_n and Y_n are the amplitude of the cosine and sine components of order-n harmonic. The vectorial notation of Eq. 2 is given in Eq. 5.

$$f(t) = W^T \cdot x(t) \tag{5}$$

where

$$W^T = [X_1 Y_1 X_2 Y_2 \ldots\ldots X_N Y_N] \tag{6}$$

$$X(t) = \begin{pmatrix} \cos(w_1 t) \\ \sin(w_1 t) \\ \cos(w_2 t) \\ \sin(w_2 t) \\ \ldots. \\ \ldots. \\ \cos(w_N t) \\ \sin(w_N t) \end{pmatrix} \tag{7}$$

The signals are sampled at a uniform rate Δt, so time values are discrete, $k\Delta t$ with k = 0, 1, 2…. The dot product presented in Eq. 20 is carried out by one Adaline neuron, where WT is the network weights vector. After the initial estimation, an adaptive algorithm updates the weights. Thus, the estimated signal converges to the actual one. Figure 1 shows the network topology and the weights update algorithm. At time *k*, $x(k)$ is the proposed signal model and factual is the actual signal. The neurons, taking into account their weights W(k), carry out an estimation $f_{est}(k)$. The error $e(k)$ is the difference between the actual signal and its estimation. An Adaline algorithm allows the weights to be used in the next iteration $W(k + 1)$ to be obtained, which minimizes that error. After this iterative process, the estimated signals adapt to the actual signals. In adaptive neural network technique, number of inputs for the neural net depends on the number of harmonics to be estimated. Total number of inputs required for the estimation of 7 harmonic terms is 14 since each harmonic term requires two inputs, one for sine value and other for cosine value. The learning rate is taken as 0.1. The waveform to be estimated is sampled with the frequency of 3,200 Hz and hence the total number of samples given is 64.

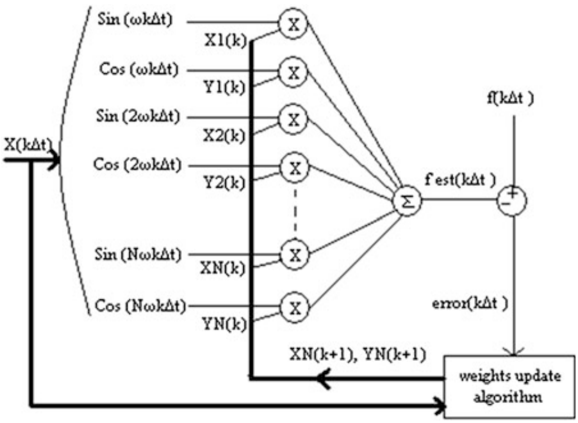

Fig. 1 Adaptive network topology

b. Shannon Entropy

Entropy in information theory is a measurement unit of information based on probability-statistic model, which can show the complexity and disorder degree of information. When a disturbance occurs, the signals' magnitude and frequency will change and its entropy will change correspondingly. In this way, we can detect disturbance by entropy variety. Equations 8–10 explain the concept of difference entropy.

$$D(n) = f'(n+1) - f'(n), n = 0, 1....N-2 \tag{8}$$

$$p_n = p_{[D(n)]=\frac{\text{abs}[(n)]}{\sum \text{abs}[D(n)]}} \tag{9}$$

$$H(n) = -\sum_{n=1}^{L} p_{n\log_2(p_n)} \tag{10}$$

The six different signals considered for detection are ideal sine wave, interruption in the signal for few milliseconds, voltage sag, voltage swell, impulse in the signal for few milliseconds, and oscillations transients. These six signals will possess the characteristics of the following equations

Ideal sine waveform

$$f(t) = A\ \sin(\omega t) \tag{11}$$

Interruption

$$f(t) = [1 - \alpha(f(t_2 - t_1))]\sin(\omega t) \tag{12}$$

where $\alpha > 0.9$ is amplitude change factor; $0.5T < t_2 - t_1 < 3$ s is durative time of disturbance.

Voltage sag

$$f(t) = [1 - \alpha(f(t_2 - t_1))]\sin(\omega t) \tag{13}$$

where $\alpha = 0.1 \sim 0.9$ is amplitude change factor; $0.5T < t_2 - t_1 < 30T$ is durative time of disturbance.

Voltage swell

$$f(t) = [1 + \alpha(f(t_2 - t_1))]\sin(\omega t) \tag{14}$$

where $\alpha = 0.1 \sim 0.8$ is amplitude change factor; $0.5T < t_2 - t_1 < 30T$ is durative time of disturbance.

Impulse

$$f(t) = \sin(\omega t) + \alpha[f(t_2) - f(t_1)] \tag{15}$$

where $\alpha = 1 \sim 3$ is amplitude of impulse; 1 ms $< t_2 - t_1 <$ 3 ms is durative time of disturbance.

Oscillation transient

$$f(t) = \sin(\omega t) + \alpha e^{-c(t-t1)}\sin(\beta\omega t)[f(t_2) - f(t_1)] \tag{16}$$

where $\alpha = 0.1 \sim 0.8$ is amplitude of oscillation; $\beta = 0.1 \sim 0.5$ is fluctuation frequency relative coefficient; c is damped oscillations coefficient; $0 < t_2 - t_1 < 2T$ is durative time of disturbance.

3 Results and Discussions

Test signals are generated using MATLAB software using Eqs. 11–16. The sampling frequency is assumed 4 kHz and three full wave is considered for analysis. PQ disturbances are created between 25 and 37.5 ms.

The proposed algorithm is applied to determine the starting and ending instants of the disturbances present in the practical voltage signal. The consumer units in distribution systems have inductive and nonlinear characteristics. These nonlinear

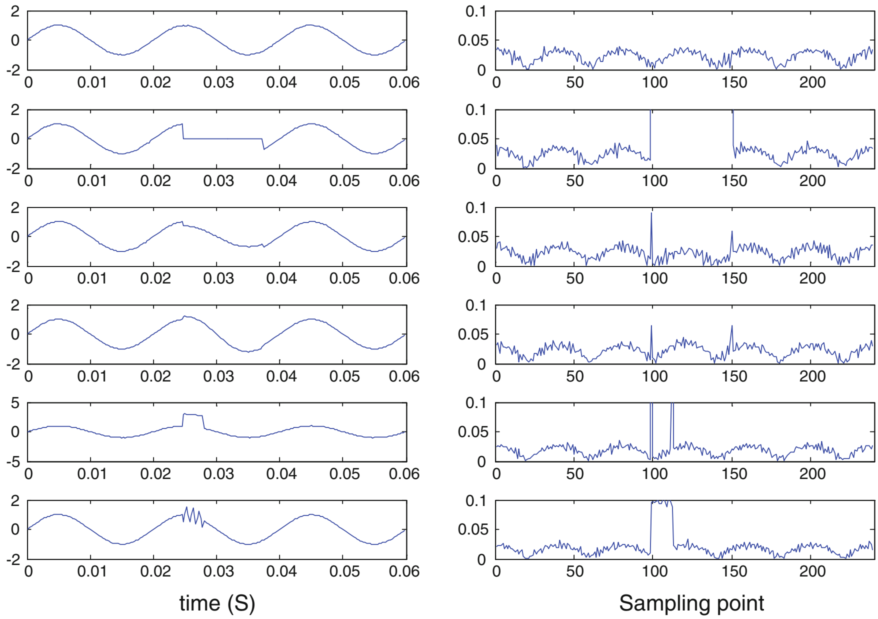

Fig. 2 Test signals and their entropy without harmonics

loads inject harmonic currents of several orders into utility electric system leading to non-sinusoidal situations. Hence, it becomes necessary to analyze the signal including harmonics. If the Shannon entropy alone is applied for the signals in the presence of harmonics, simulations show that the time of transient disturbances cannot be obtained. Hence, adaptive neural network-based harmonic detection algorithm is initially used to split up the harmonics present throughout the signal and Shannon entropy is applied for the signal after removing the harmonics.

Figure 2 shows the entropy for the six signals considered in the absence of harmonic components. The sampling frequency is fixed as 4 kHz. Figure shows the signal with harmonics and the results of ANN algorithm (Fig. 3 and Table 1).

The signal is distorted with a THD of 11.5 %. After the estimation of harmonics, the signal is split up into individual harmonics. The harmonics are summed up and the value of harmonics at each sampling point is determined. The harmonic components are determined using the following equation.

$$\mathrm{HC} = \sum_{k=1}^{N} A_k \sin(w_k t + \varphi_k) - A_1 \sin(w_1 t + \varphi 1). \tag{17}$$

where HC is harmonic component. HC is an array of values at each sampling point. These components are fixed constant and will be extracted from the signal to remove the harmonics for entropy estimation. Difference entropy for ideal sine wave is distributing average implying that there is no disturbance in it. The

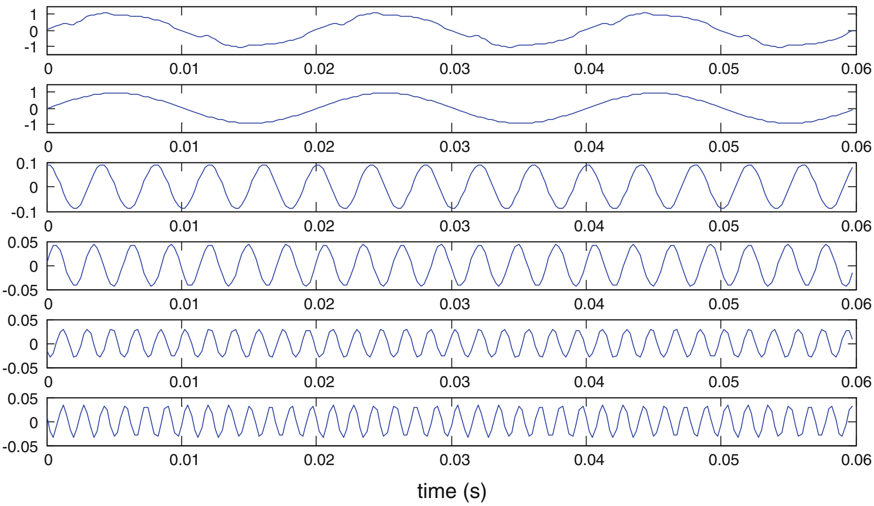

Fig. 3 Output waveforms from ANN module

Table 1 Results from ANN

Harmonics (h)	1	3	5	7	9	11	13
Magnitude (p.u)	0.950	0.000	0.090	0.043	0.000	0.030	0.033
Phase angle (rad)	−0.0353	0.0000	1.4329	0.1379	0.0000	−2.5674	2.837

difference entropy value increases drastically in the instant of disturbance. Figures 5 and 6 show the variation in entropy for different noise values. The starting instant and ending instants of a disturbance occurring in a signal can be recorded accurately and effectively using the proposed method (Fig. 4).

a. Effect of noise in detection

Random noise is added to the signal with various signal-to-noise ratio ranges from 40db to 8db. The simulation results are given for noises of 40 and 10 db. From the results, it is obvious that the noise plays important role in the performance of ANNDE method in Fig. 5. The stronger noise heavily affects the performance of the method.

b. Effect of amplitude in detection

From the figure, it is seen that the sharp thresholds are obtained using ANNDE method even in the presence of noise. The method failed to obtain the disturbing instants in some cases in the presence of noise. When voltage sag magnitude is around 0.9, the proposed method is not able to feature out the sag. Also for voltage swell, the magnitude around 1.1 is undiscoverable. All values except the stated are discoverable. Table shows a summary of exhaustive simulations done (Table 2).

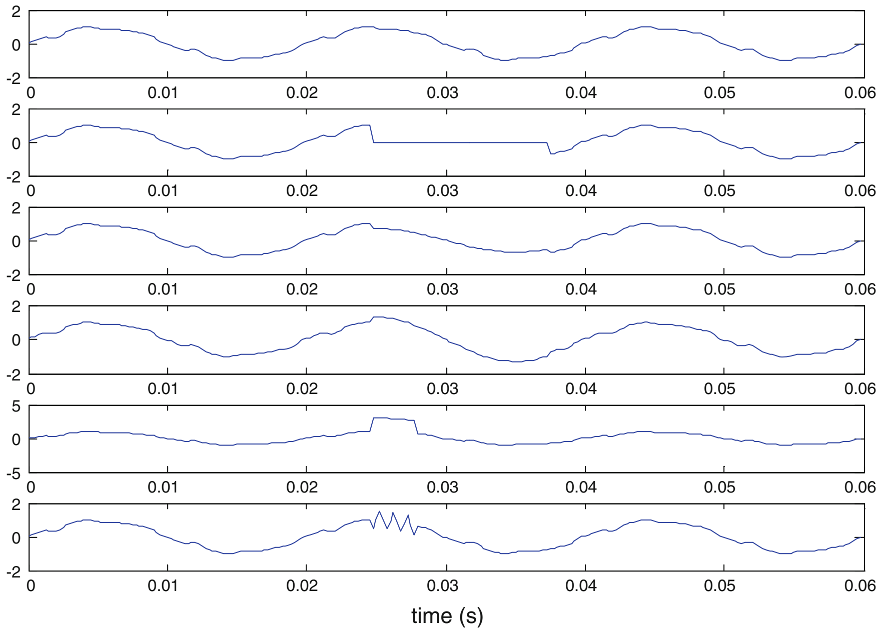

Fig. 4 Test signals with harmonics

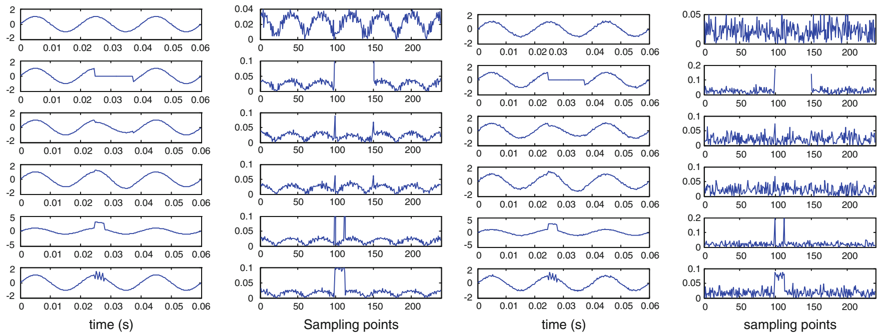

Fig. 5 Test signals with harmonics and their entropy at 40 and 10 db

Table 2 Summary of exhaustive simulations

S. No	Disturbances	Noise	Amplitude	Begin instant detection	End instant detection
1	Interruption	db > 10	0	√	√
2	Voltage sag	db > 15	a > 0.85	x	x
			0.1 ≤ a ≤ 0.85	√	√
3	Voltage swell	db > 15	1.1 ≤ a ≤ 1.8	√	√
4	Impulse	db > 10	1 ≤ a ≤ 3	√	√
5	Oscillation transient	db > 10	0.1 ≤ a ≤ 0.8	√	√

4 Conclusion

Power quality disturbances detection methodology based on ANN and Shannon difference entropy algorithm is proposed in this paper. Vast simulations are done to validate the method adaptableness and found that the performance of the algorithm is better than the conventional algorithms. ANN extracts the harmonics present in the signal and difference entropy algorithm can extract characteristic hiding in the signals. The proposed method has good noise resistance ability. The algorithm is simple and easy to implement in real time.

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