A new approach to monitoring electric power quality

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Abstract

The paper presents an adaptive neural network approach for the estimation of harmonic distortions and power quality in power networks. The neural estimator is based on the use of linear adaptive neural elements called adalines The learning parameter of the proposed algorithm is suitably adjusted to provide fast convergence and noise rejection for tracking distorted signals in the power networks. Several numerical tests have been conducted for the adaptive estimation of harmonic components, total harmonic distortions, power quality of simulated waveforms in power networks supplying converter loads and switched capacitors. Laboratory test results are also presented in support of the performance of the new algorithm

Keywords: Neural network; Electric power quality; Harmonic distortions

1. Introduction

Power quality is a term that is directed at a wide variety of variations in the electric power supplied to utility customers. These variations can originate and/or manifest themselves at various places in the power network. Many of these power quality concerns are associated with the operation and design of customer facilities, concerns associated with wiring and grounding problems, switching transients, load variations, and harmonic generations, etc.

The proliferation of power electronic devices and computer loads are directly linked to the increasing number of power quality related problems. Not only are these types of loads a source of additional harmonics, but they also have a high sensitivity to non-sinusoidal waveforms. As a result, the use of power quality analysis methodologies and measurement tools is becoming commonplace in the power industry. Estimation of harmonic components in a power or distribution network supplying nonlinear loads and solid state switching devices is a standard approach for the assessment of the quality of delivered power. The identification of harmonics is important where harmonic standards are to be adopted. It may be used to allocate loads that exceed specified harmonic current limits. Furthermore, it is an important requirement for designing harmonic filters.

Most frequency domain harmonic analysis techniques [1,2] use discrete Fourier transform (DFT) or fast Fourier transform (FFT) to obtain harmonic estimates of distorted signals. In applying FFT, the phenomena of aliasing, leakage and picketfence effects may lead to inaccurate estimates of harmonic magnitudes. The DFT suffers from inaccuracies due to the presence of random noise usual in the measurement process and tracking of signals with time varying amplitude and phase involves large errors. The application of Kalman filters and recursive LMS and RLS filters [3–5] have been reported in the literature for tracking time varying signals embedded in random noise and decaying dc components. Both these filters suffer from large computational overhead and suitable values of covariance matrices and real-time implementation of these filters poses difficult problems.

This paper presents a new approach [6,7] for the estimation of harmonic amplitudes and phase, total harmonic distortions, and harmonic powers and a power quality index using a single adaptive neuron called adaline. An adaline has a set of input, and a desired response signal. It has also a set of adjustable

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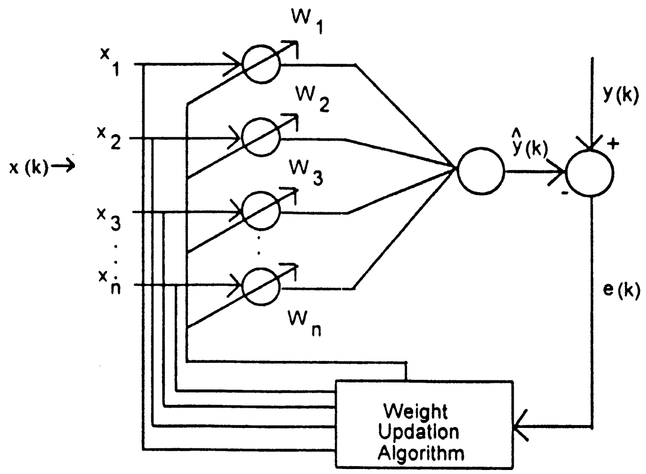


Fig. 1. Block diagram of an adaline.

parameters called the weight vector. The weight vector of the adaline generates the Fourier coefficients from a distorted signal using a nonlinear weight adjustment algorithm based on a stable difference error equation. Several computer simulation tests are conducted to estimate the harmonic amplitudes, and phase, THD and harmonic powers from distorted power system signals. The proposed estimation technique is adaptive and is capable of tracking the variations of amplitude and phase angle of the harmonics. The performance of this algorithm is compared with the widely used Kalman filtering technique due to its simplicity, superior noise rejection and tracking performance. Further tests in the laboratory are conducted to track the voltage and current harmonics, harmonic power and distortions, etc. of a R–L load supplied through power converters using the new neural estimation approach.

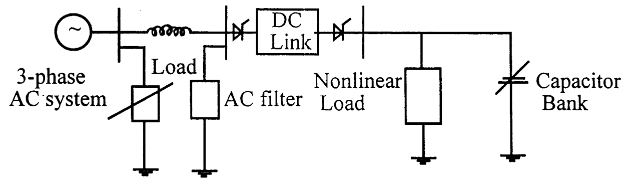


Fig. 3. Schematic diagram of model used for simulation study.

2. Adaline for harmonic estimation

The power system voltage or current waveform is assumed to comprise fundamental and harmonic components as

$$y(t) = \sum_{i=1}^{N} A_i \sin(i\omega t + \phi_i) \tag{1}$$

where the A_i's and ϕ_i's are the amplitude and phase of the harmonics, respectively; N is the total number of harmonics, and ω is the angular frequency of the fundamental component of the signal. To obtain the solution for on-line estimation of the harmonics, we propose the use of an adaptive neural estimator comprising an adaptive neuron called Adaline which is shown in Fig. 1.

To obtain the input variables for the adaline, the signal given in equation is written in the discrete form as

$$\begin{aligned} y(k) &= A_1 \cos\phi \cdot \sin\theta + A_1 \sin\phi \cdot \cos\theta + \ldots \\ &\quad + A_N \cos\phi_N \cdot \sin N\theta + A_N \sin\phi_N \cdot \cos N\theta \end{aligned} \tag{2}$$

where

$$\theta = \frac{2\pi k}{N_S} \tag{3}$$

N is the order of the highest harmonic present in the signal, k is the sample number or iteration count and N_S is the sample rate.

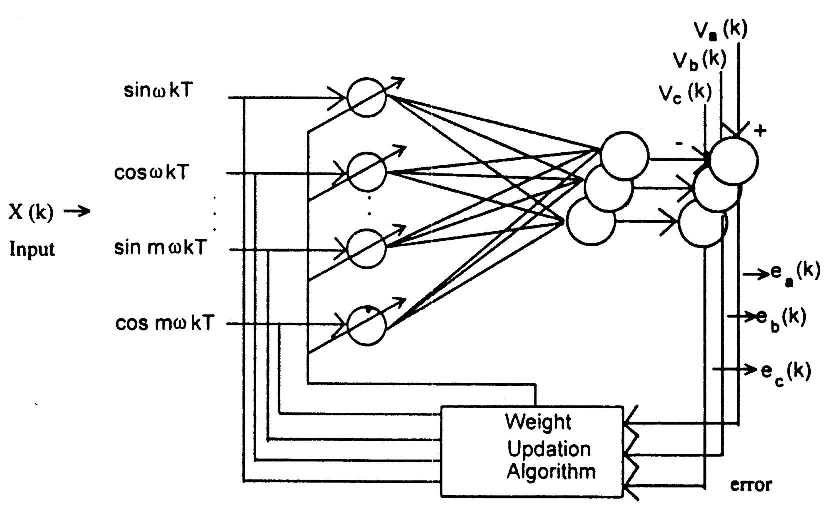


Fig. 2. Block diagram of the adaline used for tracking 3-phase voltages and currents.

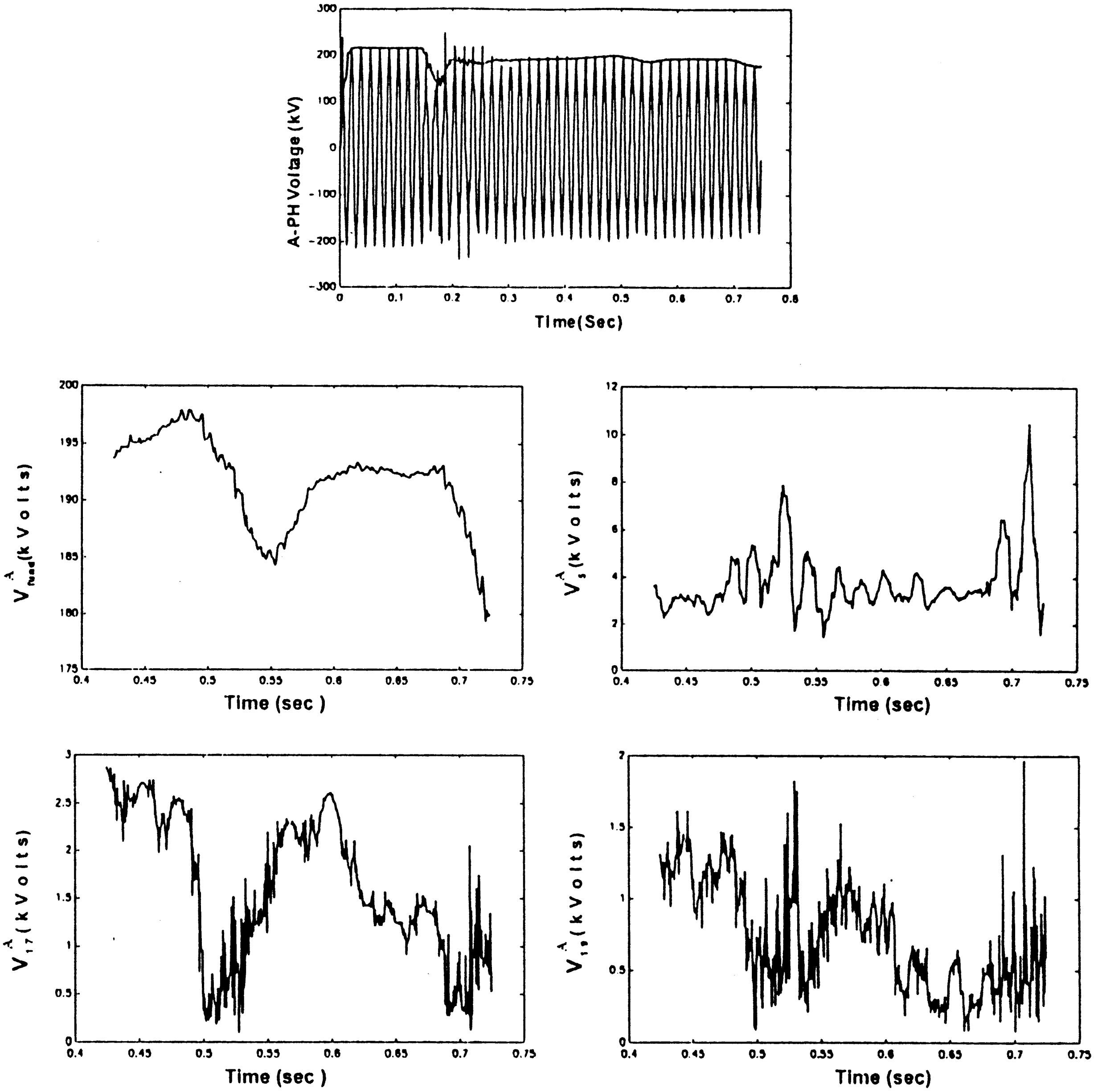


Fig. 4. Voltage waveform, fundamental and dominant harmonics of phase-A at the inverter end.

Thus, the input vector to the adaline is given by

$$x(k) = [\sin\theta \cos\theta \sin 2\theta \cos 2\theta \ldots \sin N\theta \cos N\theta]^T \tag{4}$$

where T is the transpose of the quantity.

If the power system signal contains a decaying dc component with a decaying rate of $1/\beta$, the waveform is described by

$$y(t) = A_{\mathrm{dc}} \mathrm{e}^{-\beta t} + \sum_{i=1}^{N} A_i \sin(i\omega t + \phi) \tag{5}$$

The practical value of β lies between 0.5 and 20, depending on the resistance and reactance values in the power network. A large value of β indicates a very fast decaying dc quantity. Further the value of β is not known and is identified by the linear combiner.

The signal is expressed using Taylor series expansion (neglecting higher order terms) as

$$y(t) = A_{\mathrm{dc}} - A_{\mathrm{dc}}\beta t + \sum_{i=1}^{N} A_i \sin(i\omega t + \phi) \tag{6}$$

In this the input vector to the adaline is expressed as

$$\boldsymbol{x}(k) = \left[1 \, \frac{\theta}{\omega} \sin\theta \cos\theta \ldots \sin N\theta \cos N\theta \right]^T \tag{7}$$

The weight vector of the adaline is updated using a nonlinear weight adaptation algorithm (modification of Widrow–Hoff delta rule) as

$$W(k+1) = W(k) + \frac{\alpha e(k)\, \boldsymbol{X}(k)}{\lambda + x^T(k)\, \boldsymbol{X}(k)} \tag{8}$$

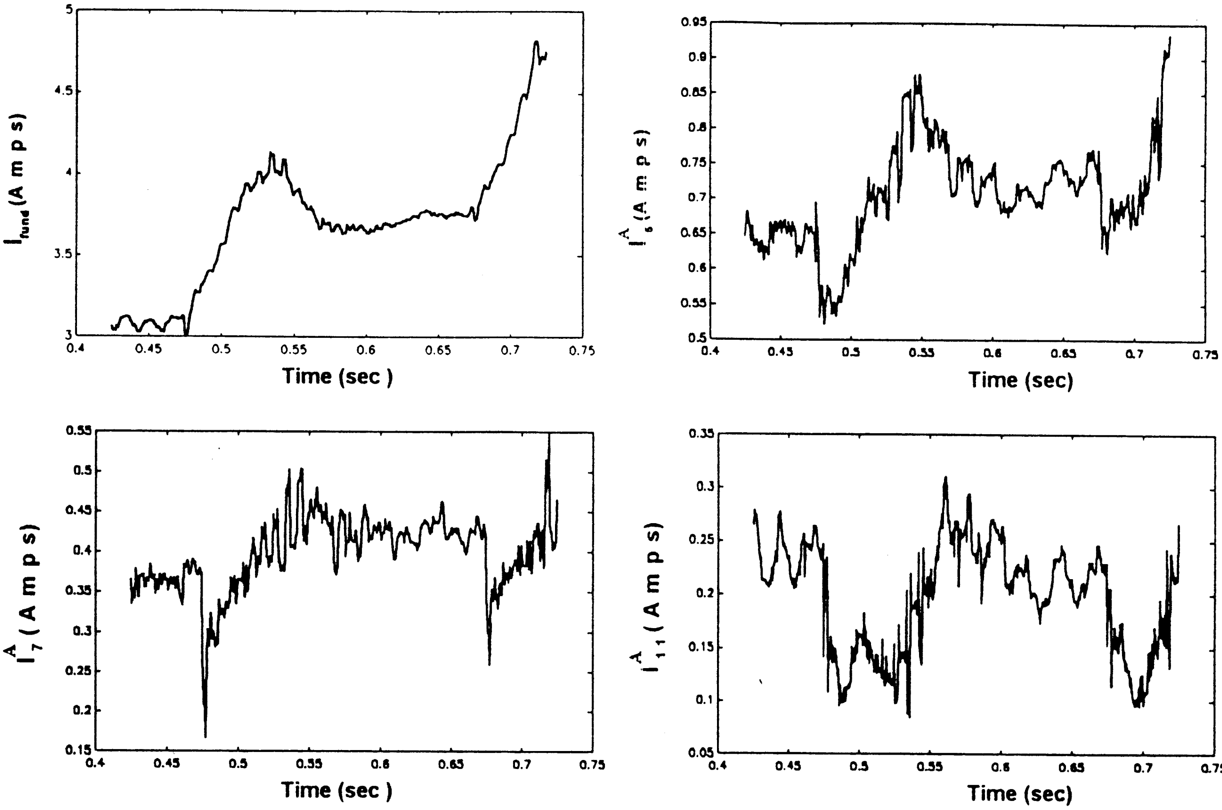


Fig. 5. Fundamental and dominant harmonics of phase-A current at the inverter end.

where the following hold good at the kth sampling instant: $\boldsymbol{x}(k)$ is the input vector; $W^T(k) = [W_1(k)\ W_2(k)\ W_3(k)\ W_4(k) \ldots\ W_{2N+1}(k)\ W_{2N+2}(k)]$; $e(k) = y(k) - \hat{y}(k)$is the error; $y(k)$ is the actual signal amplitude; $\hat{y}(k)$ is estimated signal amplitude; α is the learning parameter; and λ is a parameter to be suitably chosen to avoid division by zero.

In the above equation the vector $\boldsymbol{X}$ is chosen as

$$\boldsymbol{X}(k) = [1\ 1\ \mathrm{SGN}\ (\sin\theta)\ \mathrm{SGN}\ (\cos\theta) \ldots\ \mathrm{SGN}(\sin N\theta)\ \mathrm{SGN}(\cos N\theta)]^T \quad (9)$$

and the SGN function of a variable $x_i(\cos\theta, \sin\theta, \ldots, \cos N\theta, \sin N\theta$, etc.) is given by

$$\mathrm{SGN}(x_i) = \begin{cases} +1 & \text{if } x_i > 0 \\ -1 & \text{if } x_i < 0 \end{cases}$$

$i = 3, \ldots, 2N + 2$

Instead of using SGN function we can use tanh or arc(tanh) function for $\boldsymbol{X}$(k).

The error e(k) between the actual signal and the estimated signal is brought down to zero, when perfect learning is attained and the weight vector will yield the Fourier coefficients of the signal. If $\boldsymbol{W}_0$ is the weight vector after the final convergence is reached, the Fourier coefficients are obtained as

$$\boldsymbol{W}_0 = [A_{\mathrm{dc}}\ \beta A_{\mathrm{dc}}\ A_1 \cos\phi_1\ A_1 \sin\phi_1 \ldots A_N \cos\phi_N\ A_N \sin\phi_N]^T \quad (11)$$

The amplitude and phase of the Nth harmonic are given by

$$A_N \sqrt{\boldsymbol{W}_0^2(2N+1) + \boldsymbol{W}_0^2(2N+2)}$$

and

$$\phi_N = \tan^{-1}\left[\frac{\boldsymbol{W}_0(2N+2)}{\boldsymbol{W}_0(2N+1)}\right] \quad (12)$$

The learning parameter α used in the modified Widrow–Hoff delta rule is an important parameter which controls the convergence and noise rejection property of the neural estimator. The learning parameter α adapted recursively in the following way:

$$\alpha(k+1) = \mu\alpha(k) + \gamma \left\| e(k) \right\|^2 \quad (13)$$

where the initial value of α ($\alpha(0)$) is chosen to lie between $0 < \alpha(0) < 2$ and the forgetting factor $\mu = 0.97$. The value of γ is chosen appropriately between $0.001 < \gamma < 0.1$ for rapid convergence to reduce the Euclidean distance between $W(k)$ and $\boldsymbol{W}_0$. A value of $\gamma = 0.01$ is suitable for tracking harmonics in power networks. The learning parameter α is, however, constrained to lie between the limits

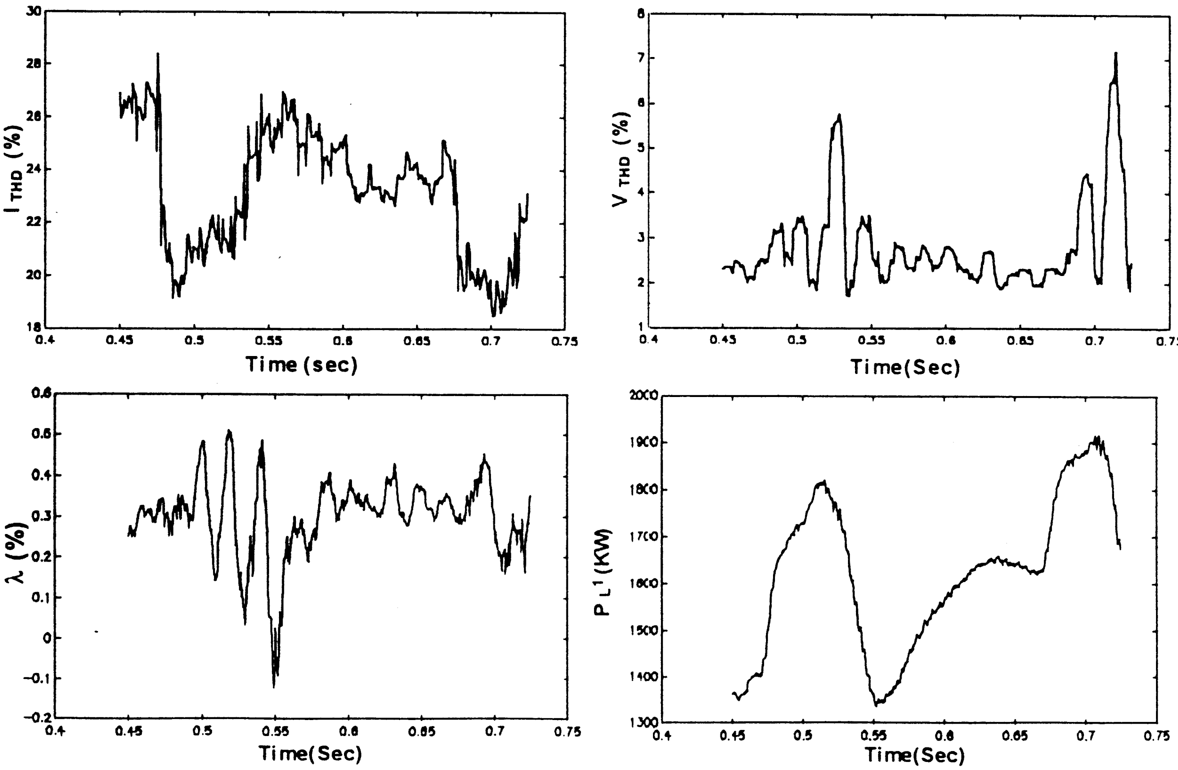


Fig. 6. Measured power quality indices.

$$\alpha_{\min} \leq \alpha(k+1) \leq \alpha_{\max} \tag{14}$$

The choice of $\alpha_{\min}$ and $\alpha_{\max}$ is to be done in such a way that

$$0 < \alpha_{\min}, \alpha_{\max} < 2 \tag{15}$$

The step size is always positive and is controlled by the size of the prediction error and the parameters μ and γ. For a large prediction error, the learning parameter is increased to provide faster tracking. The parameter $\alpha_{\max}$ is so chosen as to ensure the mean square error of the algorithm remains bounded and $\alpha_{\min}$ is so chosen as to provide a minimum level of tracking ability. The parameter μ is usually chosen in the range of 0–1 to provide exponential forgetting of the system data.

The power system signal model presented in Eq. (5) does not show any noise term. Thus, if a random noise is added to the signal model, the accuracy of the neural estimator will be affected in the presence of random noise. Thus, to provide a better noise rejection term, the error term is fed back recurrently and the input to the adaline will become for the model containing dc component and harmonics as

$$\boldsymbol{x}(k) = \left[1 \ \frac{\theta}{\omega} \sin\theta \cos\theta \ldots \sin N\theta \cos N\theta \ e(k) \ e(k-1) \ e(k-2) \right]^T \tag{16}$$

3. Harmonic distortion factor and harmonic power

After the amplitude and phase of the fundamental and harmonic components are estimated, it is necessary to compute the voltage and current distortion factors as

$$V_{\text{THD}} = \frac{\sqrt{\sum_k V_k^2}}{V_1}, \qquad I_{\text{THD}} = \frac{\sqrt{\sum_k I_k^2}}{I_1} \tag{17}$$

and

$$k = 0, 2, 3, \ldots, \infty$$

where V_1 and I_1 are the RMS values of the fundamental frequency components of voltage and current, respectively.

The V_{THD} factor is considered a good index of the supply quality and I_{THD} ($I_{\text{THD}} > 0$) is effective in the identification of a polluting load.

The fundamental and harmonic active power of the power network are obtained from Eq. (18) as

$$P = \boldsymbol{W}_{0v}(3) \cdot \boldsymbol{W}_{0i}(3) + \boldsymbol{W}_{0v}(4) \cdot \boldsymbol{W}_{0i}(4)$$

$$P_N = \boldsymbol{W}_{0v}(2N+1) \cdot \boldsymbol{W}_{0i}(2N+2) + \boldsymbol{W}_{0v}(2N+1) \cdot \boldsymbol{W}_{0i}(2N+2) \tag{18}$$

where $\boldsymbol{W}_{0v}$ and $\boldsymbol{W}_{0i}$ are the converged weight vector for voltage and current samples of the network. The total harmonic active power is obtained as

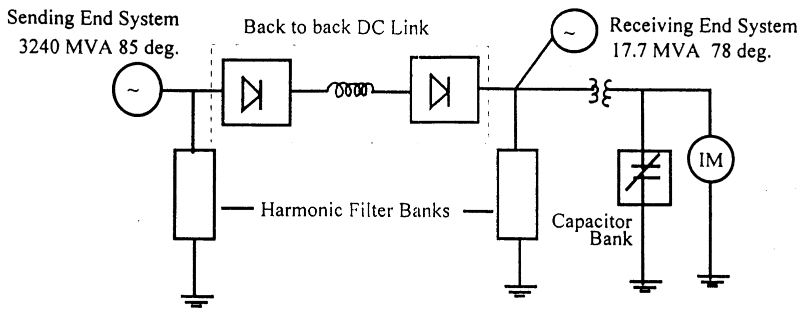


Fig. 7. (i) Load current waveform, (ii) dc and harmonic components and (iii) I_{THD} of a half-wave rectifier.

$$P_m = \sum_{n=2}^{N} P_n \tag{19}$$

The active harmonic power is considered as an index of the presence of a polluting load and its effects on power quality.

For a 3-phase three-wire system, the instantaneous positive and zero voltage and current space vector are defined as:

Positive sequence:

$$V_{\mathrm{p}} = \frac{2}{3}\left[V_{\mathrm{a}N} + V_{\mathrm{b}N} \exp\left(-j\frac{2\pi N}{3}\right) + V_{\mathrm{c}N} \exp\left(j\frac{2\pi N}{3}\right)\right] \tag{20}$$

$$i_{\mathrm{p}} = \frac{2}{3}\left[i_{\mathrm{a}N} + i_{\mathrm{b}N} \exp\left(-j\frac{2\pi N}{3}\right) + i_{\mathrm{c}N} \exp\left(j\frac{2\pi N}{3}\right)\right] \tag{21}$$

Zero sequence

$$V_{0N} = \tfrac{1}{3}\left[V_{\mathrm{a}N} + V_{\mathrm{b}N} + V_{\mathrm{c}N}\right]$$

$$i_{0N} = \tfrac{1}{3}\left[i_{\mathrm{a}N} + i_{\mathrm{b}N} + i_{\mathrm{c}N}\right] \tag{22}$$

Further the instantaneous positive sequence components can be resolved into orthogonal components as

$$V_{\mathrm{p}} = V_{\mathrm{d}N} + jV_{\mathrm{q}N}$$

$$i_{\mathrm{p}} = i_{\mathrm{d}N} + ji_{\mathrm{q}N}$$

The magnitudes of $V_{\mathrm{d}N}$, $V_{\mathrm{q}N}$, $i_{\mathrm{d}N}$, and $i_{\mathrm{q}N}$ are obtained after the separation into real and imaginary parts in Eqs. (20) and (21).

For each phase of the power network, the voltages $V_{\mathrm{a}N}$, $V_{\mathrm{b}N}$, $V_{\mathrm{c}N}$ are computed using one neural estimator as

$$V_{\mathrm{a}N} = \left[\boldsymbol{W}_{0v\mathrm{a}}^2(2N+1) + \boldsymbol{W}_{0v\mathrm{a}}^2(2N+2)\right]^{1/2} \tag{23}$$

where

$$\phi_N = \tan^{-1}\left[\frac{\boldsymbol{W}_{0v\mathrm{a}}(2N+2)}{\boldsymbol{W}_{0v\mathrm{a}}(2N+1)}\right]$$

$$V_{\mathrm{b}N} = \left[\boldsymbol{W}_{0v\mathrm{b}}^2(2N+1) + \boldsymbol{W}_{0v\mathrm{b}}^2(2N+2)\right]^{1/2}$$

$$V_{\mathrm{c}N} = \left[\boldsymbol{W}_{0v\mathrm{c}}^2(2N+1) + \boldsymbol{W}_{0v\mathrm{c}}^2(2N+2)\right]^{1/2} \tag{24}$$

$$\phi_{\mathrm{b}N} = \tan^{-1}\left[\frac{\boldsymbol{W}_{0v\mathrm{b}}(2N+2)}{\boldsymbol{W}_{0v\mathrm{b}}(2N+1)}\right]$$

$$\phi_{\mathrm{c}N} = \tan^{-1}\left[\frac{\boldsymbol{W}_{0v\mathrm{c}}(2N+2)}{\boldsymbol{W}_{0v\mathrm{c}}(2N+1)}\right]$$

The Nth harmonic power is obtained for one phase as

$$P_N = V_{\mathrm{d}N} \cdot i_{\mathrm{d}N} + V_{\mathrm{q}N} \cdot i_{\mathrm{q}N} + V_{0N} \cdot i_{0n}, \quad N > 0 \tag{25}$$

Hence the total harmonic power for all the three phases

$$P_{m=3\mathrm{ph}} = \sum_{n=1}^{N} P_{n-3\mathrm{ph}} \tag{26}$$

Another alternative form for the harmonic power can be written as

$$P_m = \mathrm{Re}\left\{\frac{1}{T}\int_0^T [V_a(t) \cdot i_{\mathrm{a}}\,\mathrm{d}t + V_{\mathrm{b}}(t) \cdot i_{\mathrm{b}}\,\mathrm{d}t + V_{\mathrm{c}}(t) \cdot i_{\mathrm{c}}\,\mathrm{d}t]\right\} \tag{27}$$

where $V_{\mathrm{a}}(t)$ and $i_{\mathrm{a}}(t)$, etc. are the instantaneous phase voltages and currents, respectively and are obtained from the neural estimation filter, one filter each for the voltage and current (six for all the three phases).

The instantaneous voltage and currents for each phase are the outputs from the neural estimator and are obtained as (as shown in Fig. 2)

$$V_{\mathrm{a}}^{\wedge}(t) = \boldsymbol{W}_{\mathrm{a}}^T X_{\mathrm{a}} \tag{28}$$

where $\boldsymbol{W}_{\mathrm{a}}$ denotes the weight vector for the A-phase voltage and X_{a} is the input Fourier component. In a similar way voltages and currents for all the phases can be computed to provide the active harmonic power for all the three phases.

If the harmonic power $P_m > 0$, this power is flowing to the load and indicates a source side pollution. On the other hand if $P_m < 0$, this is produced by the nonlinear load and the pollution is created by the load. The 3-phase power factor is given by

$$\lambda = P/S \tag{29}$$

where P is the total active power produced by the fundamental and harmonic components and $S = V \cdot I$, which is given by

$$S\left[\left(\sum_{n=1}^{N} V_{dn}\right)^2+\left(\sum_{n=1}^{N} V_{qn}\right)^2\right]^{1/2}$$
$$\times\left[\left(\sum_{n=1}^{N} i_{dn}\right)^2+\left(\sum_{n=1}^{N} i_{qn}\right)^2\right]^{1/2} \quad (30)$$

4. Simulation results

4.1. Case 1

Fig. 3 shows the schematic diagram of a power network comprising a 3-phase ac system feeding non-linear load via a dc-link. The dc link supplies power to a 3-phase ac system with a time-varying load and variable static capacitor bank at the load end. The converter is switched on at $t=0.12$ s and load changes are effected at $t=0.45$, 0.65 and 0.75 s by 0.2, 0.4 and -0.5 pu, respectively. The voltage and current waveforms are monitored at the load testing point of the ac-system. Numerical simulation is performed using the EMTDC [8] software package, which is capable of simulating power networks during transient conditions.

The instantaneous voltage waveform is tracked using the neural estimator and is shown in Fig. 4. The corresponding fundamental and dominant voltage harmonic components of the A-phase are shown in the same figure. Fig. 5 shows the fundamental and dominant harmonic components of the phase A current at the inverter bus. The voltage and current harmonic distortions V_{THD}, I_{THD}, power quality index λ, and fundamental component of real power are shown in Fig. 6. From Fig. 4, it is seen that one cycle (based on 50 Hz waveform) is almost required to provide an accurate tracking of the peak value of the fundamental component of the phase voltage. However, when capacitor switching and load changes occur at the converter bus, harmonics are generated and the fundamental peak voltage at the converter bus reduces. Under these circumstances the neural estimator produces accurate estimates of corresponding fundamental and harmonic components. The switching operations of the converter load and the load and converter bus capacitors generate large amounts of voltage and current distortions, which can be observed from the figure. The performance of the Kalman filter in tracking the harmonics and distor tions is found to be inferior in comparison to the proposed neural estimator. This has also been confirmed in Ref. [6] and the results of this comparison are omitted here.

4.2. Case 2

The second test case taken for numerical simulation is a 15 000 HP induction motor fed from a strong ac system via a back-to-back power converter system (rectifier and inverter connected back-to-back). A switching capacitor bank is installed across the induction motor terminal for power factor improvement. Fig. 7 shows the schematic diagram of the studied system. The following three operations are carried out sequentially:

1. dc link starting at 0.085 s;
2. induction motor starting at 0.12 s;
3. the capacitor bank is switched on at 0.16 s.

Fig. 8 shows the fundamental, 5th, 7th and 11th harmonic voltages for A-phase along with voltage and current THDs, and power quality index using the adaptive neural estimator.

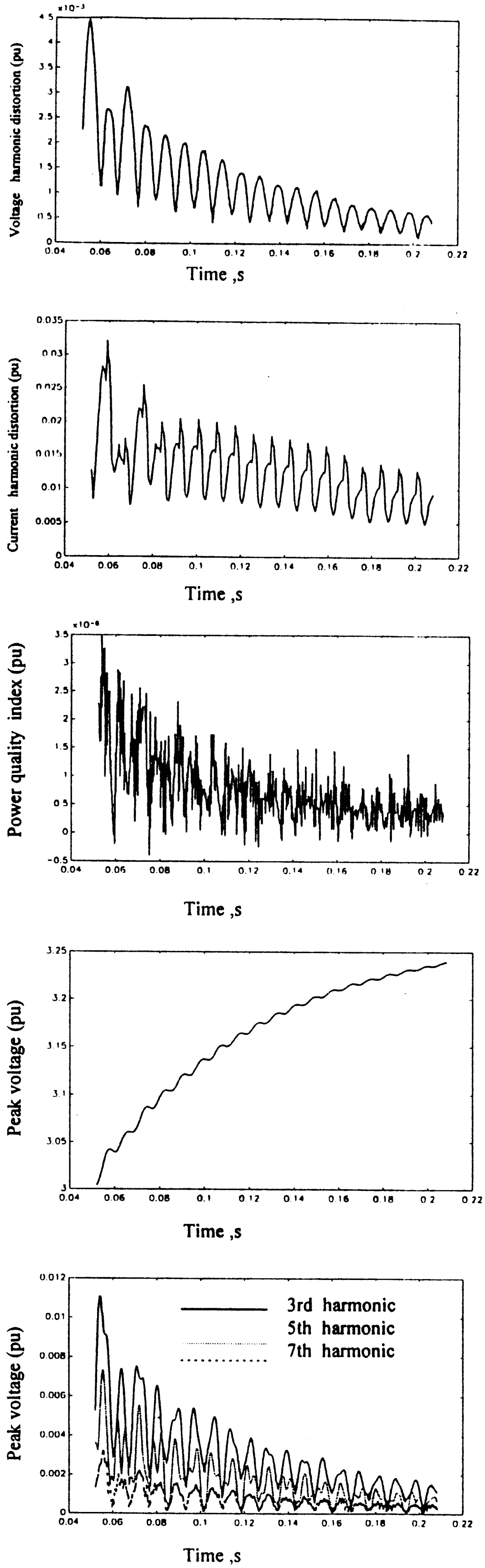
4.3. Real-time monitoring of power quality

With a view to real-time implementation of the proposed neural estimator for power quality assessment, data is obtained from a laboratory setup comprising a 230 v, 50 Hz, ac system supplying a R–L load through a half-wave or a full-wave rectifier. The resistance and inductance of the load are $R=330\ \Omega$ and $L=0.05$ H. The power supply waveform was checked by an oscilloscope, which was found to be practically sinusoidal without any significant harmonic content.

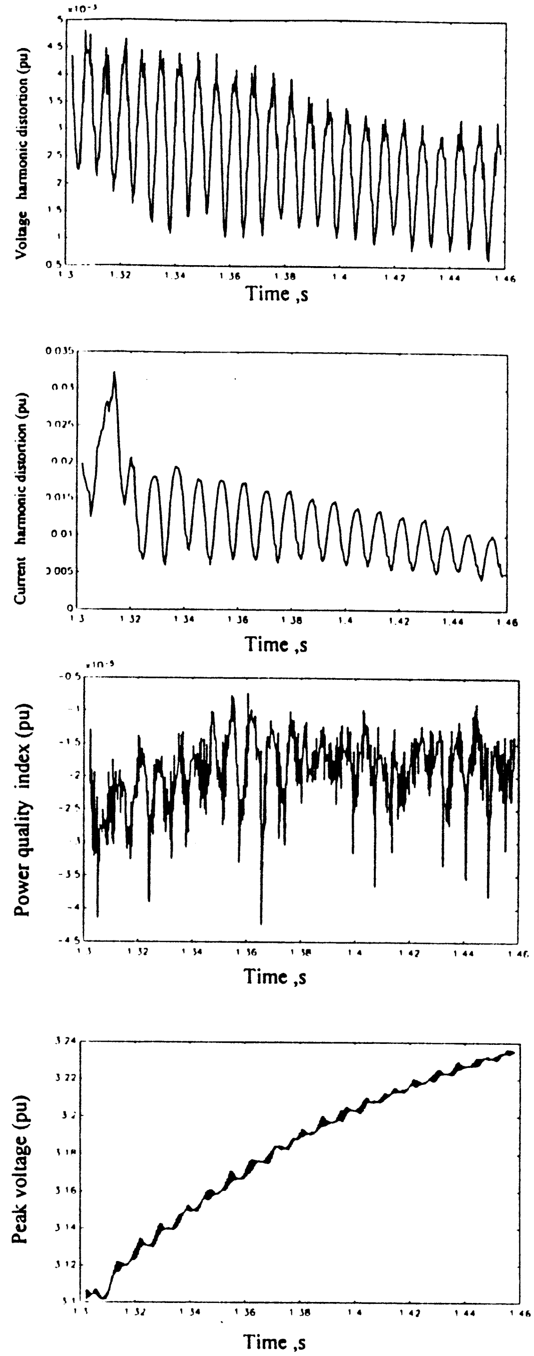
The system data is acquired through a PCL-718 data acquisition card using a 12-bit successive approximation technique for A/D conversion. The card provides a powerful and easy to use software driver routine. A personal computer PC-486, 66 MHz processor is used to process the voltage and current samples using a software program written in C^{++} language. The sampling time is fixed at 0.25 ms, thus giving a sampling rate of 4 kHz. The PC-486 processor is fast enough to provide very fast execution time in a real-time environment and in this case the program is executed in less than 0.1 ms, thus giving the possibility of a larger sampling rate. The neural estimator with an adaptive learning parameter α provides fast tracking of the fundamental component of the voltage. The harmonic components for the R–L load supplied by half-wave and full-wave rectifiers are shown in Figs. 9 and 10. From the figures it is observed that once the neural estimator is initialised, the tracking is found to be fast and accurate for successive changes. The total current harmonic distortions are also shown in the figures.

5. Conclusions

The single-layer adaptive neural network presents a very realistic and promising approach for fast estimation of power network signal parameters corrupted by noise, decaying dc components and harmonics. The



(i) Tracking during charging of DC link



(ii) Tracking during induction motor startup

Fig. 8. (i) Input current waveform, (ii) harmonic components and I_{THD} of a full-wave rectifier.

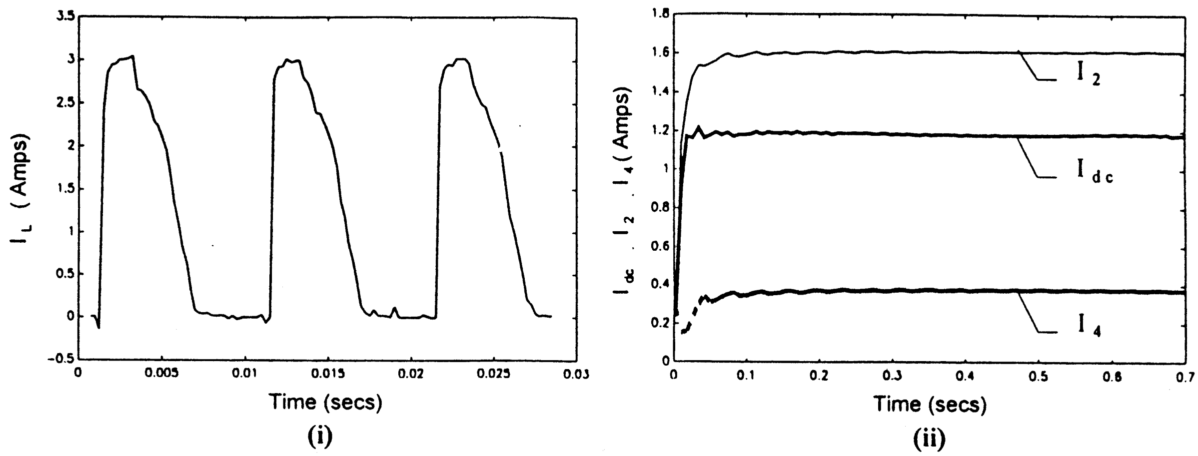


Fig. 9. (i) Load current waveform, (ii) dc and harmonic components, and (iii) I_{THD} of a halfwave rectifier.

non-linear adaptation of the weight vector for the adaline is performed using a difference error equation and provides an accurate estimation of amplitude and phase of the 3-phase voltage and current phasors corrupted by harmonics and noise. The learning parameter α is also adapted for providing fast convergence and noise rejection. Numerical simulation tests using the EMTDC software package clearly demonstrate the capability of the algorithm in quantifying power quality from noisy data. Real-time laboratory tests confirm the validity of the new approach for computing harmonic distortions and power quality on-line.

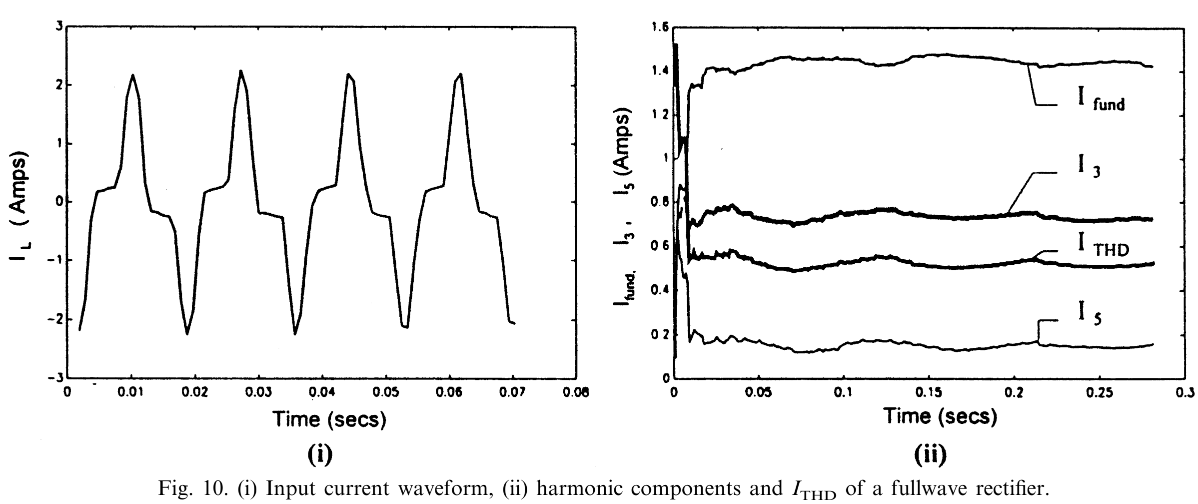


Fig. 10. (i) Input current waveform, (ii) harmonic components and I_{THD} of a fullwave rectifier.

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References

[1] G.H. Hostetter, Recursive discrete Fourier transformation, IEEE Trans. Acoust. Speech Signal Process. 28 (1980) 180–184.
[2] E. Oran Brigham, The Fast Fourier Transform and Its Applications, Prentice Hall, Englewood Cliffs, NJ, 1988.
[3] P.K. Dash, A.M. Sharaf, A Kalman filtering approach for estimation of Power system harmonics, in: Proceedings of the 3rd International Conference on Harmonics in Power Systems, Nashville, IN, September 28–October 1, 1988, pp.34–40.
[4] A.A. Girgis, W.B. Chang, E.B. Makram, A digital measurement scheme for on-line tracking of power system harmonics, IEEE Trans. Power Delivery 6 (3) (1991) 1153–1160.
[5] I. Kamwa, R. Granin, Fast adaptive schemes for tracking voltage phasor and local frequency in power transmission and distribution systems, IEEE Trans. Power Delivery 1 (2) (1992) 789–795.
[6] P.K. Dash, D.P. Swain, A.C. Liew, S. Rahman, An adaptive linear combiner for on-line tracking of power system harmonics, IEEE Trans. Power Appar. Syst. 96WM 181–8 PWRS, January 21–25, 1996.
[7] B. Widrow, M.A. Lehr, 30 years of adaptive neural networks: perceptrons, madaline and backpropagation, IEEE Proc. 78 (1990) 1415–1442.
[8] EMTDC User Manual, Manitoba HVDC Research Centre, Winipeg, Manitoba, Canada.