Fast Non-Recursive Extraction of Individual Harmonics Using Artificial Neural Networks

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Abstract

Non-linear loads, which cause harmonic distortion, are increasingly being used in electrical power systems. This is causing a major concern and real-time harmonic monitoring in electrical power systems has become important. Many applications such as harmonic monitoring and filter design need techniques for fast extraction of individual harmonic components. The time limitations and computational complexity associated with conventional techniques make it appealing to investigate new techniques for harmonic extraction. This paper presents a novel technique based on artificial neural networks (ANN) for fast extraction of individual harmonic components. It uses the non-linear mapping capabilities of ANNs to accurately estimate individual harmonic components of a distorted signal. The proposed algorithm was implemented on a real-time hardware platform and tested. Results show that the Artificial Neural Network based Harmonic Extractor (ANNHE) is significantly faster and less computationally complex than conventional techniques.

1. Introduction

The assumption that the electrical supply at the customers' mains is a set of balanced sinusoidal voltage sources is never fully reached in practice. The sinusoidal shape of the voltage waveforms gets deformed due to the flow of current signals other than those at fundamental frequency, which are mostly generated by non-linear loads connected to the system. These steady-state periodic waveforms, which deform the supply signal, are termed as harmonics. Harmonics in power systems cause losses, inconvenience and sometimes serious problems to the consumer as well as to the power system [1-4].

Recent few years have witnessed rapid growth in harmonic voltages and currents injected into the power system due to the increased utilisation of non-linear loads. In addition, devices employing high frequency switching, such as switch mode power supplies (SMPS) in televisions, computers and compact fluorescent lighting add a significant level of harmonics to the supply system. Although voltage distortion at the transmission level is typically much less than 1.0 percent, this distortion increases closer to the load point. At some loads, the current waveform will barely resemble a sine wave. As a result, harmonic distortion is more pronounced at the distribution level.

The effects of increasing harmonic levels in electrical power systems have triggered several issues regarding the quality of the supply. One such issue is adaptation of harmonic standards such as G 5/4 (Limits for harmonics in the UK electricity supply system)[4], to set limits on the harmonic pollution. According to these standards, the end users must limit the harmonic currents injected into the power system. These standards require that consumers should maintain the harmonic current generated by their loads below some specified values. To adequately deal with the harmonic distortion in electrical power systems, and to comply with the above recommendations, it is of the utmost importance to monitor the harmonic levels. Conventional techniques used for harmonic monitoring employ either frequency domain or time domain harmonic extraction techniques.

Discrete Fourier Transform (DFT) and Fast Fourier Transform (FFT) are usually used for calculating the harmonic content of a periodic signal. Although the FFT is fast in terms of computing speed, it needs data points sampled over one cycle of the signal to accurately calculate the harmonic components. Therefore, the time required to extract the harmonic component depends on the fundamental frequency of the signal being analyzed. This is a major drawback when analysing signals with low frequencies. Since the fundamental frequency of electrical power system signals is 50 Hz or 60 Hz typically, harmonic extraction takes 20 ms or 16.67 ms, respectively. Also, the perversion of FFT or DFT would yield inaccurate results, due to pitfalls such as aliasing, leakage and picket fence effect [5]. In addition, the FFT can be considered as a more general approach to harmonic extraction, where all the harmonic frequency components within the band-width of the signal is calculated. This makes the FFT processor hardware more expensive as more computational power is required. However, many applications, such as harmonic monitoring, may require extraction of a limited number of individual harmonics. For an example, in many cases only the 5th and 7th harmonics are of interest as the levels of other harmonic components are significantly low.

Time domain techniques for harmonic extraction mainly uses digital filter techniques such as Infinite Impulse Response (IIR) filters. Although, these can be used to extract individual harmonic components, the ripple and time delay inherited in these filters make them less appealing. Also, practical difficulties in implementing the ideal filter characteristics make the design process of these filters much more complicated.

More recent research efforts revolve around proposing alternative techniques for harmonic extraction. The digital recursive measurement scheme for on-line tracking of power system harmonics proposed by Girgis et al [6] uses a Kalman Fitler (KF) to estimate the harmonic components. It is reported that the method presented is capable of tracking harmonics even with time varying amplitudes. In this method, the distorted signal is state space modelled with harmonic components as state variables. Then, a KF based technique is applied to estimate the harmonic components. The KF algorithm is more accurate than the FFT and it is also capable of extracting individual harmonics. However, one of the major drawbacks of this method is that the KF has to be formulated for all possible frequencies expected. Omission of any frequency component at the formulating phase of the KF will lead to inaccurate results. Also, this method needs correct definition of state equations, measurement equations and covariance matrices.

The "subspace" methods such as min-norm method and Prony method are discussed by Leonovicz et al [7]. It has been shown that the min-norm method could be effectively used for parameter estimation of distorted signals and Prony method could also be applied for estimating the frequencies of signal distortion. However, the computational complexity of these methods is much more than that of the FFT whilst the time taken for harmonic extraction is similar. The use of ANNs for real-time harmonic monitoring has been the focus of many researchers [8-11]. ANNs provide simple and straightforward techniques for selectively tracking individual harmonic components. However, in all these methods the ANN is not used in its pure form, where an input is fed to the ANN and an output is taken. Rather, they use the training algorithm of ANNs, which recursively estimate the harmonic components. Due to the recursive nature of harmonic estimation, results published so far indicate significantly slower response, even less than the FFT. Also, the need for sinusoidal waveform generators at different frequencies makes the hardware realisation more complex.

This paper proposes a method based on feed forward ANNs, which is significantly faster than the FFT. Also, it requires less computational power allowing it to be implemented even on low-end microcontrollers, which reduces the hardware implementation costs significantly. ANNs basically use addition and multiplication operations, which can be implemented more easily on microcontrollers, as compared to calculation of sine and cosine functions in the FFT and calculation of matrix inversion in the Kalman Filter.

2. Formulation of the ANN

2.1 Artificial Neural Networks (ANN)

A feed forward multi-layered ANN can be considered as a flexible mathematical structure which is capable of identifying complex non-linear relationships between input and output data sets. For these reasons ANN models have been found useful and efficient, particularly in problems for which the characteristics of the process are difficult to describe using mathematical equations. ANNs are powerful objects having inference and generalisation capabilities; in fact, an ANN that has been trained with a representative number of examples of a given process is able to extrapolate states not present in example data set.

An ANN consists of simple processing elements known as neurons. The inputs to the ANN are weighted and processed by each neuron. Initially, a neural network has to be trained using a set of input data representing possible inputs to the network and the desired output data. In this process, the weight of each neuron is adjusted to minimise the output error. After training, unknown input data can be presented to the neural network and corresponding output data are obtained. In any given application, selection of appropriate parameters as input and output of the network is the key to the success and optimal performance of the neural network. Therefore, in the case of power system harmonic extraction, the first task would be to formulate the problem and the selection of a suitable set of input and output parameters.

2.2 Problem formulation

A voltage or current signal $s(t)$ that is distorted with harmonics can be modelled as:

$$s(t) = \sum_{k=0}^{N} V_k \sin(k\omega t + \phi_k) \qquad (1)$$

where V_k and ϕ_k are the amplitude and phase angle of the kth harmonic component, respectively. The proposed system samples the signal $s(t)$ at a sampling frequency f_s and the time discrete signal $S(n)$ is obtained, where $n = 0, 1, 2, \ldots$ etc. Then, M time delayed samples from $S(n)$ are fed to the ANN as shown in Figure (1). Therefore, the input to the ANN is a column vector X given by:

$$X = [S\{n-(M-1)\} \quad S\{n-(M-2)\} \quad \ldots \quad S(n-1) \quad S(n)]^T \qquad (2)$$

A minimal value for M is desired, as it will determine the time taken to extract the harmonic. However, it should be large enough to give the ANN a sufficient number of inputs and hence improved accuracy.

The output of the ANN, $Y_k(n)$, is a function of the input vector X and the weights associated with neurons W. Therefore,

$$Y_k(n) = f(X,W) \tag{3}$$

The desired output of the ANN, $Y_k(n)_d$, is the extracted k^{th} harmonic component and is given by:

$$Y_k(n)_d = V_k \sin\left(\frac{k\omega n}{f_s} + \phi_k\right) \tag{4}$$

The output error (ε) is,

$$\varepsilon = Y_k(n)_d - Y_k(n)$$

$$\therefore \varepsilon = V_k \sin\left(\frac{k\omega n}{f_s} + \phi_k\right) - f(X,W) \tag{5}$$

Least Mean Square (LMS) algorithm used for training ANNs is based on an approximate steepest descent procedure. In this method, the adjustment to the i^{th} weight $\left(W^{(i)}\right)$ is estimated by using the partial derivative of the squared error with respect to the i^{th} weight. That is [12]:

$$W^{(i)}{}_{new} = W^{(i)}{}_{old} - \alpha \frac{\partial \varepsilon^2}{\partial W^{(i)}} \tag{6}$$

where α is a parameter used for tuning the learning process (typically α is between 0 and 1). Substitution from equation (5) in equation (6) yields:

$$W^{(i)}{}_{new} = W^{(i)}{}_{old} - \alpha \frac{\partial \left(V_k \sin\left(\frac{k\omega n}{f_s} + \phi_k\right) - f(X,W)\right)^2}{\partial W^{(i)}}$$

$$\therefore W^{(i)}{}_{new} = W^{(i)}{}_{old} + 2\alpha \left(V_k \sin\left(\frac{k\omega n}{f_s} + \phi_k\right) - f(X,W)\right) \frac{\partial f(X,W)}{\partial W^{(i)}} \tag{7}$$

The iteration is continued until ε reaches a predetermined error goal.

2.3 Implementation of the ANN

A multilayer feed forward ANN with 5 neurons at the input layer and 1 neuron at the output layer is implemented as shown in Figure (1). The ANN is trained using a signal containing time-varying 3rd, 5th, 7th, 11th and 13th harmonic components. Also, the training signal was contaminated with 1% r.m.s. white noise and the fundamental frequency of the signal also varied in the range 50 ± 1.0 Hz in order to make the ANN robust for noise and frequency variations encountered in typical power systems. The signal to be analysed is sampled at 6400 Hz, which is found to be sufficient to all the significant harmonic components up to 64^{th} harmonic. Separate ANNs were trained for extracting each individual harmonic component. Experiments revealed that when the number of input samples $M < 31$, the ANN does not reach the set error goal of 10^{-6}. Therefore, M is set to 31 where the ANN converged to the set error goal.

When the ANN was tested with data which are different from the data used for training, results produced were inaccurate. This problem was analysed and identified as the "over fitting" problem associated with ANNs [12]. This problem results when weights are converged to local minima during the iteration of equation (7). To resolve the problem, an additional output $Y_k^+(n)$ is introduced as shown in Figure (2), which ensures that the weights converge in the correct direction.

Let,

$$Y_k^+(n) = f^+(X, W) \tag{8}$$

and,

$$Y_k^+(n)_d = V_k \cos\left(\frac{k\omega n}{f_s} + \phi_k\right) \tag{9}$$

The adjustment to the i^{th} weight $\left(W^{(i)}\right)$ is estimated by using the partial derivative of the sum of the squared error with respect to the i^{th} weight as given by equation (10).

$$W^{(i)}{}_{new} = W^{(i)}{}_{old} - \alpha \frac{\partial \mathrm{E}^2}{\partial W^{(i)}} \tag{10}$$

where,

$$E^2 = \left(V_k \sin\left(\frac{k\omega n}{f_s} + \phi_k \right) - f(X,W) \right)^2 + \left(V_k \cos\left(\frac{k\omega n}{f_s} + \phi_k \right) - f^+(X,W) \right)^2 \tag{11}$$

Therefore,

$$W^{(i)}{}_{new} = W^{(i)}{}_{old} + 2\alpha \left(\left(Y_k(n)_d - f(X,W)\right) \frac{\partial f(X,W)}{\partial W^{(i)}} + \left(Y_k^+(n)_d - f^+(X,W)\right) \frac{\partial f^+(X,W)}{\partial W^{(i)}} \right) \tag{12}$$

The over fitting problem of the ANN is eliminated by this modification. As an additional bonus, computation of the amplitude of k^{th} harmonic component (V_k) becomes straight forward as,

$$V_k = \sqrt{Y_k(n)^2 + Y_k^+(n)^2} \tag{13}$$

It worth pointing out that the total harmonic distortion (THD) may be calculated using the r.m.s. values of dominant harmonic components, as determined by equation (13). Also, if a reference time is defined, the phase of the harmonic component can be calculated by using equations (4) and (9).

3. Experimental Results

3.1 Laboratory setup

The ANN modules were implemented on a dSPACE DS1103 real-time hardware platform controlled by Matlab Simulink. The test signals were generated in the laboratory by superimposing known harmonic components on a 50 Hz signal.

Amplitude of the fundamental and the harmonic components were changed and both the actual and estimated components were measured and recorded using TDS3034, 300 MHz Digital Oscilloscope.

3.2 Extraction of harmonic components

Figure (3) shows extraction of the fundamental, 5th and 7th harmonics from 50 Hz signals distorted with 5^{th}, 7^{th}, 11^{th} and 13^{th} harmonic components and 1% white noise. The sampled signal, actual component and extracted components are illustrated.

The results show that the amplitude and phase of the extracted individual harmonic components are equal to that of the actual signal. Also, it can be seen that the ANNHE response to the changes in the individual harmonic components is relatively fast.

3.3 Effect of frequency variation

The effect of the variation of the fundamental frequency on the accuracy of the ANN based harmonic extractor is observed and analysed using simulated data in Matlab-Simulink platform. Figure (4) shows the actual and estimated 5^{th} harmonic component of a signal with a fundamental frequency of 51 Hz.

To quantify the effect of frequency variation, the percentage r.m.s. error, as defined by equation (14), is used. The % error at different frequencies between 48-50 Hz is given in Figure (5).

$$Root\ Mean\ Square\ Error\ (\%) = \frac{\sqrt{\int \left(v(t)_{actual} - v(t)_{estimated} \right)^2}}{v_{actual}(r.m.s.)} \times 100 \qquad (14)$$

The results show that during normal frequency variations (50 Hz ±1%), the extracted harmonic component only slightly varies from the actual harmonic component.

4. Discussion

The ANNHE and time domain frequency extraction techniques have been implemented in Matlab-simulink platform and response time to a step increase of the 5th harmonic component of a signal is analysed. Two common time domain harmonic extraction techniques are chosen; the IIR filter and the Kalman filter. The results of extraction using two types of IIR filters, a Kalman Filter and the proposed ANNHE technique are presented in Figure (6), for comparison.

The results described in this paper demonstrate that the proposed ANNHE technique is capable of accurately extracting harmonic components from a distorted signal. In addition, it is shown that the proposed method is faster than other time-domain harmonic extraction techniques considered; see Figure (6). It should be noted that although the response time of IIR filters can be reduced by lowering the order, the ripple associated with them is usually a major concern [6]. The Kalman filter seems to provide a much faster harmonic extraction than conventional IIR filters. However, computational complexities such as matrix inversion involved in KF make it less appealing for real-time hardware implementation. The recursive nature of ANN based techniques proposed in the literature [8-11], results in a much slower response time (e.g. 35 ms [11]).

The proposed ANNHE technique is found to be robust for usual variations in the fundamental frequency. However, it is worth noting that IIR filters are more robust to variations in fundamental frequency than the ANNHE technique, as they can be designed to operate within a wider bandwidth. Nevertheless, normal variations in the fundamental frequency of electrical power systems are very small ($\pm$ 1%) which means that the technique is capable of providing adequate performance within this range.

5. Conclusions

This paper proposes a novel ANNHE to extract harmonic components from a distorted signal. The proposed ANNHE is found to be much faster than conventional techniques, such as FFT, and other techniques presented in the literature. The results obtained show that the proposed ANNHE is robust to normal variations in the fundamental frequency and noise present in the signal. The proposed ANNHE is a powerful tool that requires low-cost hardware for real-time implementation. It can be used for individual harmonic extraction in many applications in electrical power systems.

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7. List of Figures

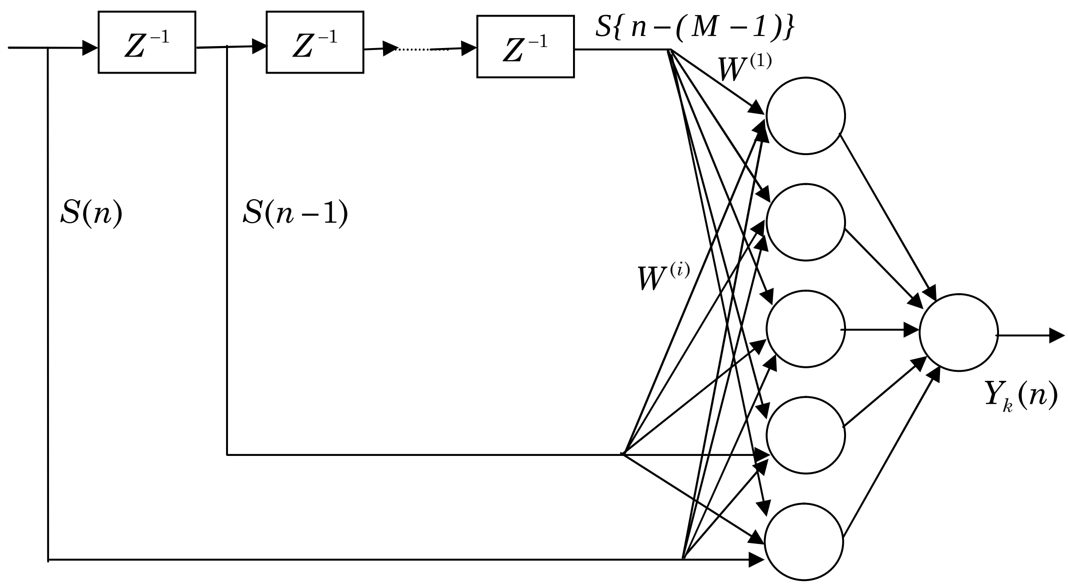


Figure (1): ANN architecture used for frequency extraction

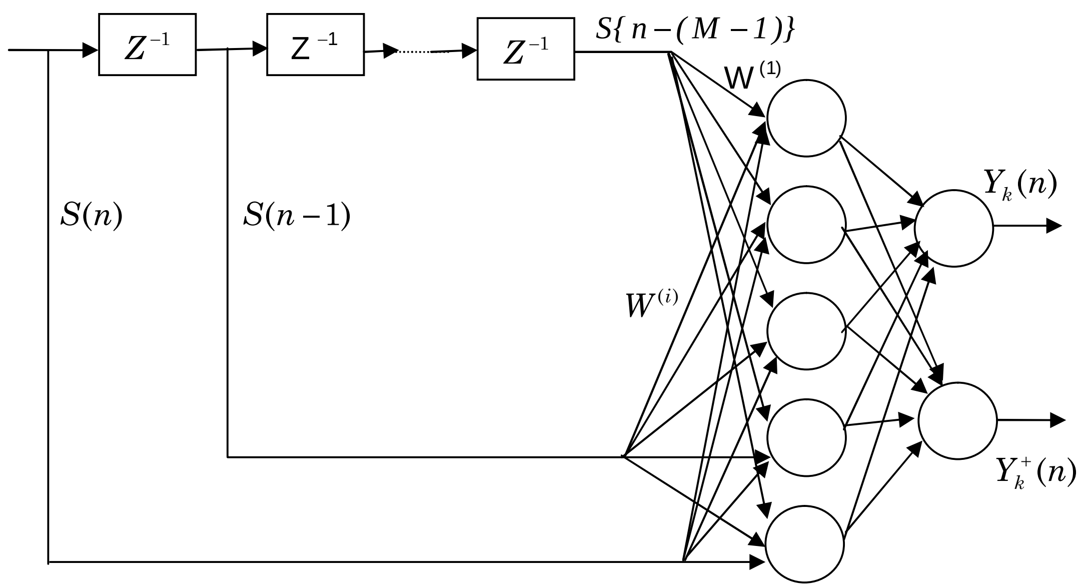


Figure (2): Modified ANN architecture

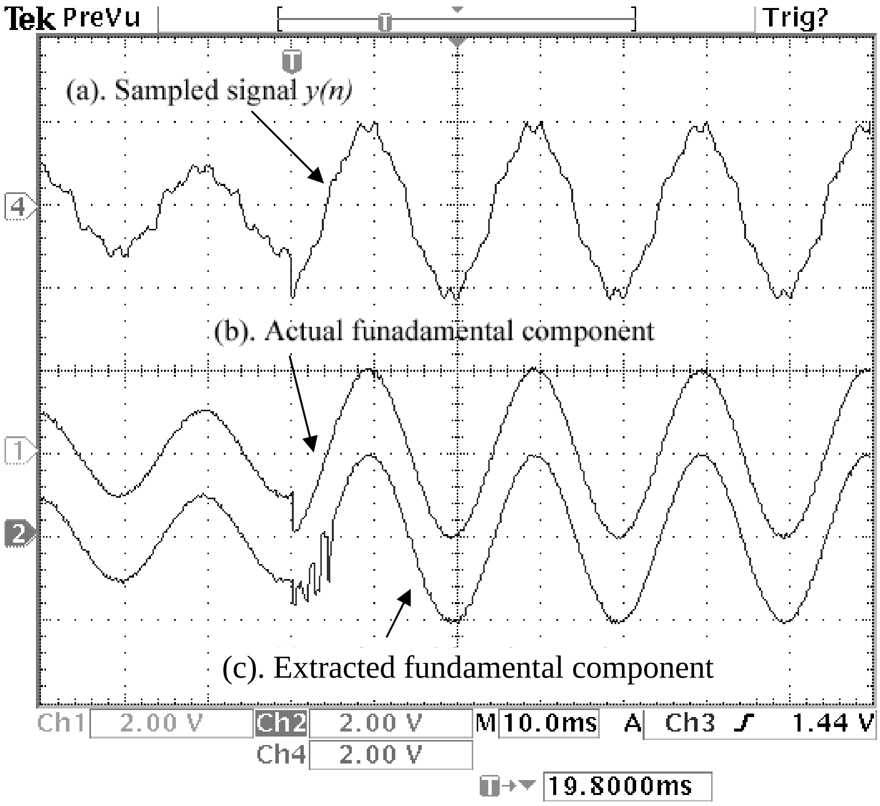


Figure 3(a): Extraction of the fundamental component

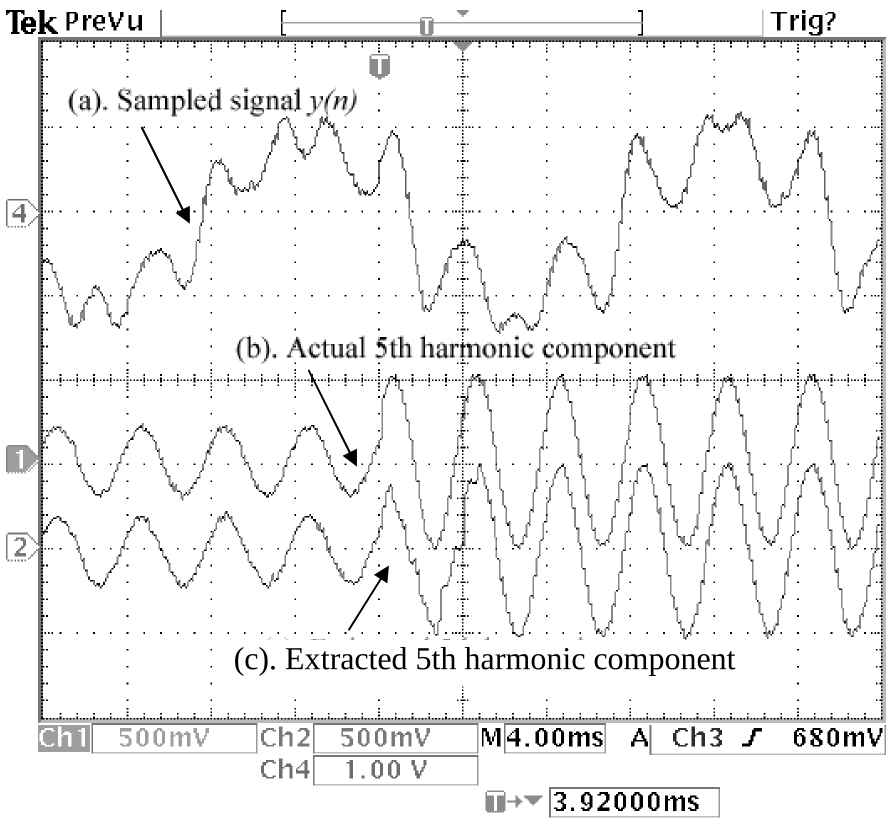


Figure 3(b): Extraction of the 5th harmonic component

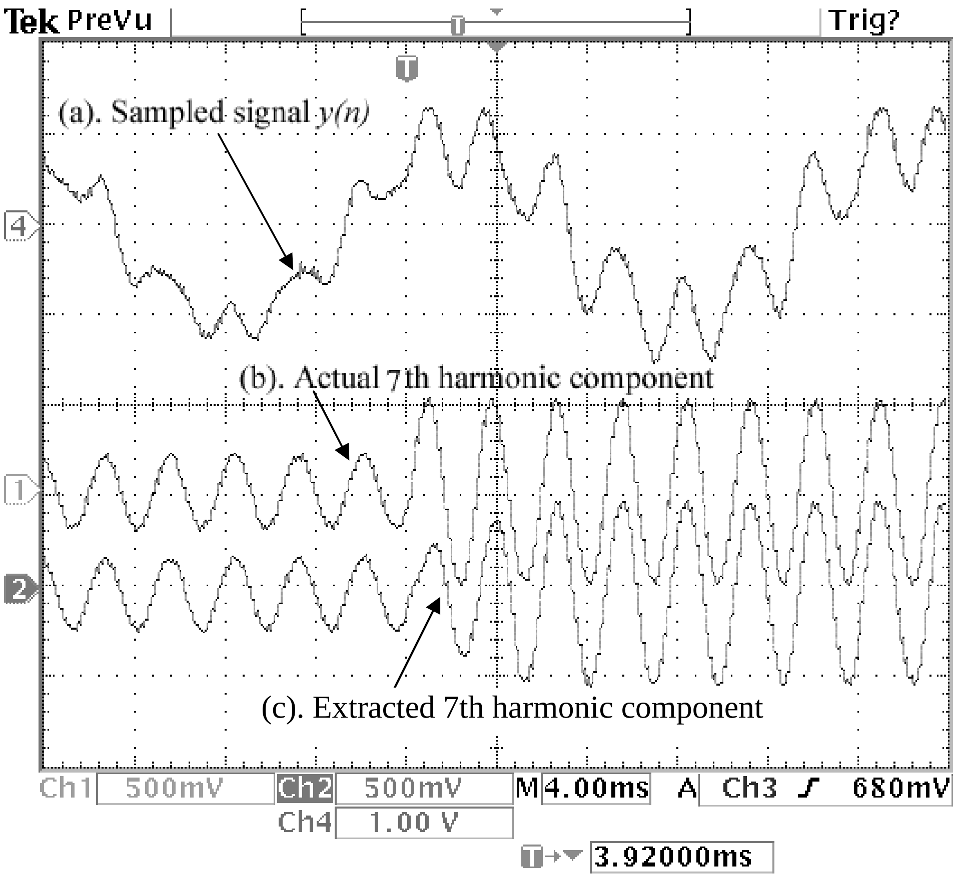
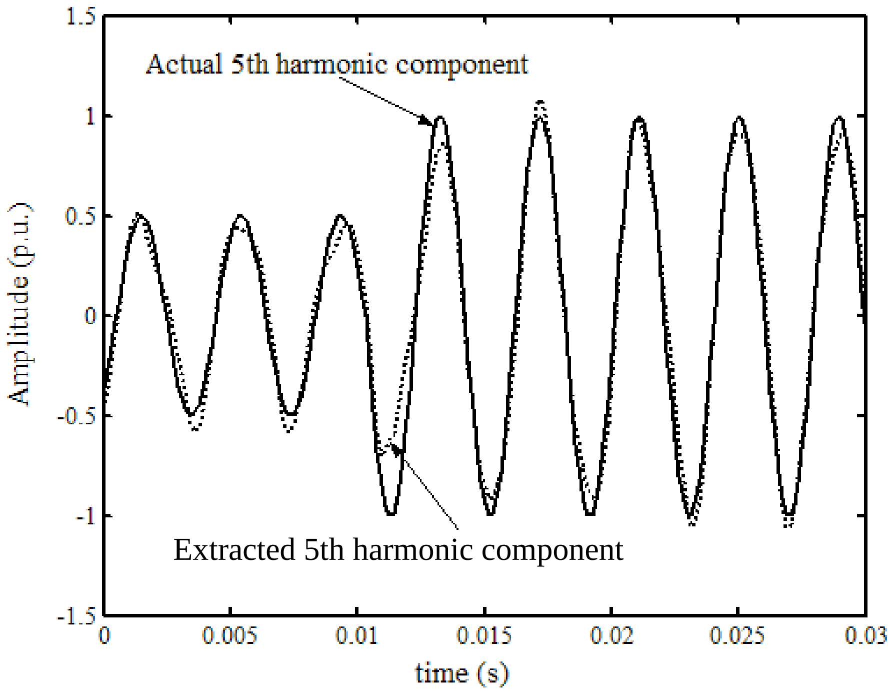
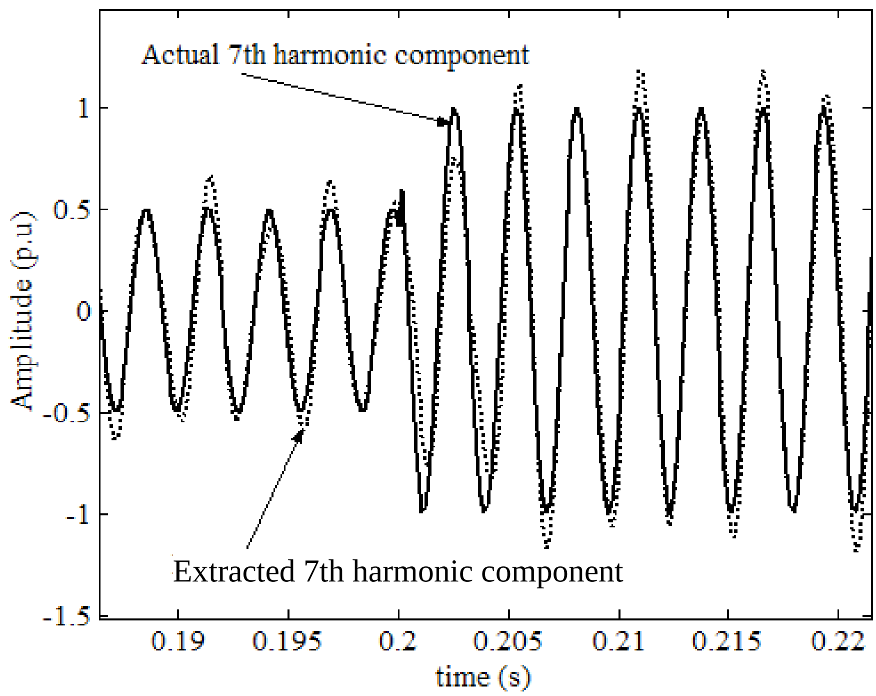


Figure 3(c): Extraction of the 7th harmonic component

Figure (3): Extraction of the fundamental, 5th and 7th harmonic components.



(a) 5th harmonic component



(b) 7th harmonic component

Figure (4): Actual and estimated (a) 5th and (b) 7th harmonic component of a signal with a fundamental frequency of 51 Hz

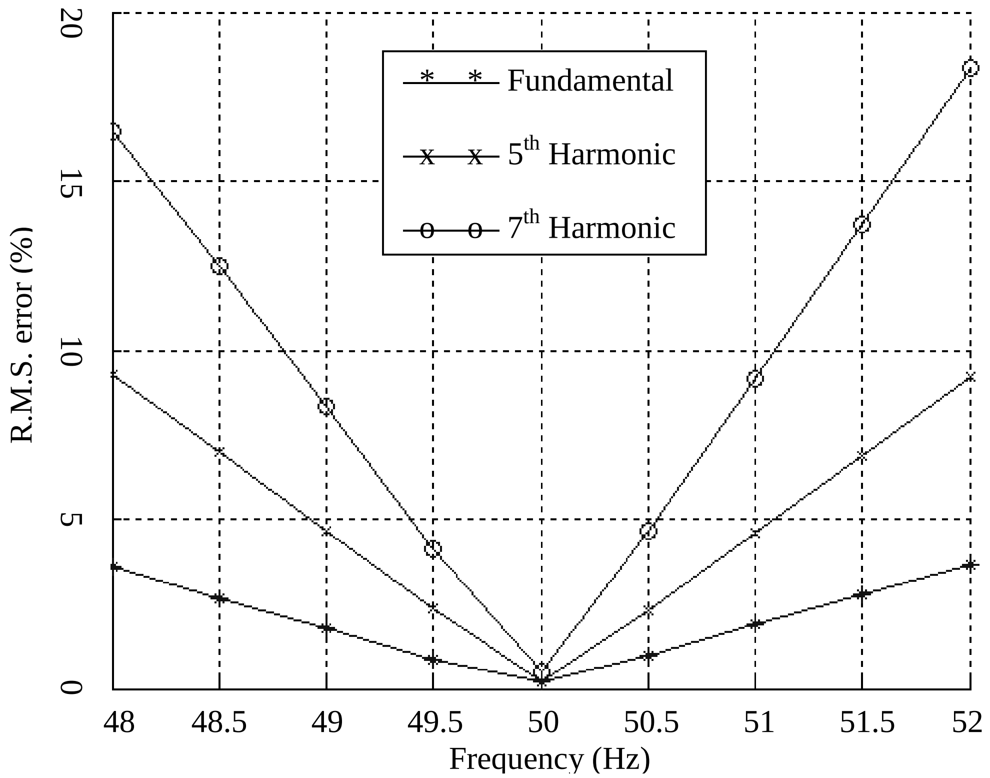


Figure (5): R.M.S. error versus frequency

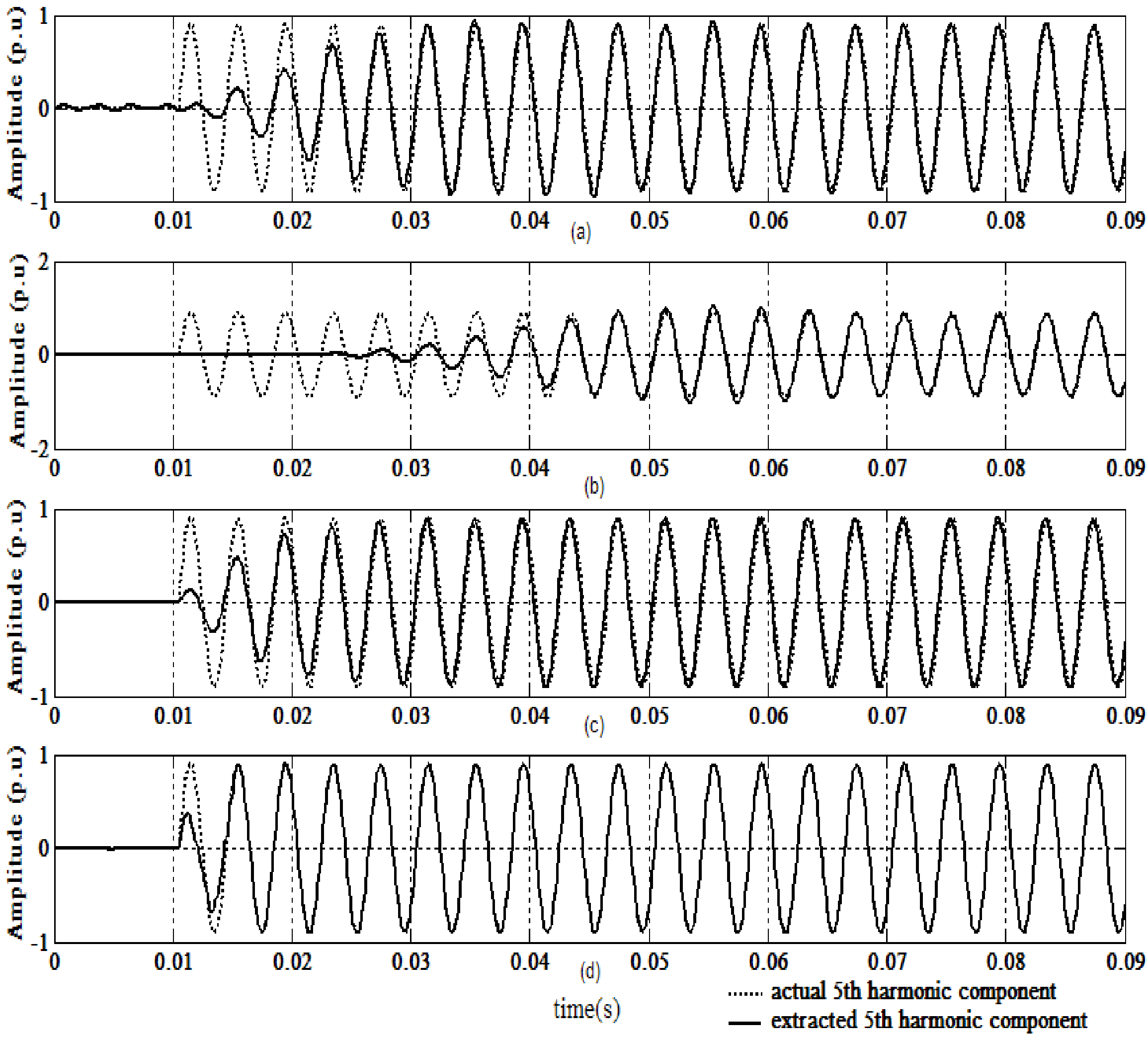


Figure (6): Time response to a step increase of 5th harmonic component in

(a) IIR filter of order 2

(b) IIR filter of order 6

(c) Kalman Filter

(d). ANNHE