Harmonics Estimation in Power Systems using a Fast Hybrid Algorithm

Zahra Moravej, and Javad Enayati

Abstract
In this paper a novel hybrid algorithm for harmonics estimation in power systems is proposed. The estimation of the harmonic components is a nonlinear problem due to the nonlinearity of phase of sinusoids in distorted waveforms. Most researchers implemented nonlinear methods to extract the harmonic parameters. However, nonlinear methods for amplitude estimation increase time of convergence. Hence, hybrid methods are used for the harmonics estimation. These methods use linear approaches for amplitude and nonlinear approaches for phase estimations. This paper focuses on introducing a fast and precise approach for harmonics estimation. This approach is based on a fast adaptive search method i.e., Adaptive Particle Swarm Optimization (APSO) for phase estimation and a linear estimator i.e., Least Squares (LS) for amplitude estimation. The speed of convergence and accuracy of estimation are the main contributions of the presented method. Obtained results by MATLAB codes indicate the accuracy and high-performance of the APSO-LS.

Keywords**—** Harmonics estimation, Adaptive particle swarm optimization (APSO), Least squares (LS).

I. Introduction

Harmonic can be defined as the undesirable components of distorted periodic waveform whose frequencies are the integral multiples of the fundamental frequency [1]. Nonlinear elements are the most common sources of harmonic distortion in a power system. Moreover, saturation phenomena in inductive elements and generation units with low quality increase original waveform distortions. Since quality of the delivered power has been one of the main requirements of power system, accurate recognition of voltage and current waveforms is essential for designing filters for eliminating or reducing the effects of harmonics in a power system [2]. Hence, estimation of harmonic parameters in a power waveform corrupted with noise has been attractive for researchers. Various methods of estimation of harmonic parameters have been examined in literature review. Time domain based methods show high quality in noise rejection compared to frequency domain methods. Consequently, they have better precision and more speed in convergence compared to frequency domain harmonic analysis algorithms. The most well known frequency domain method is discrete Fourier transform (DFT) [3-4]. However, high frequency components cause undesirable oscillation in DFT performance [5]. Also DFT has high computation burden and its process will fail when amplitudes of harmonics have abrupt changes. Linear Kalman filter approach has been successfully implemented for harmonic parameters estimation. Because of the weakness of Kalman filter based method [6] in online tracking of a signal, KF with adaptive factors was introduced in [7]. Nevertheless, Adaptive factors should be exactly tuned to able the adaptive methods to track the signal. Adaptive KF needs tuning four free parameters and also requires a priori knowledge of the noise [7]. Artificial neural network (ANN) as another alternative for harmonic estimation has been proposed in [2, 8-10]. In spite of simplicity in implementation of ANN, if the parameters of ANN are not set properly, the estimation process will converge prematurely, leading to the decline of the accuracy of the estimation results [11]. Genetic algorithm (GA) with capability of random search has been use drepeatedly to optimize the nonlinear functions [12]. This method has acceptable results in estimating the harmonic components. However, GA has the following problems for harmonic estimation:

1. Since amplitudes and phases are different quantitatively with different scales, units, and physical interpretation, it is difficult to get the homogenous genetic pool with respect to the final solution. One way could be normalizing both parameters, which even then, the magnitudes of phases and amplitudes would lie in very different regions on the number line [13].
2. The efficiency of GA is significantly degraded when it is applied to a function where the parameters that are optimized are highly correlated (in harmonic estimation, the change of the phase of the fundamental harmonic may alter the phases of other harmonics) [14].
3. The GA has difficulties in fine tuning of a local search; it spends most of the time competing between different hills, rather than improving the solution along a single hill on which the optimal point is located [15].

As another stochastic optimization technique, Particle swarm optimization (PSO) has been applied to harmonic estimation. PSO is much less dependent on

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the initial values of the variables compared to GA [16]. The PSO based methods have been found to be robust in solving problems, featuring nonlinearity and no differentiability, multiple optimization, and high dimensionality through adaptation [17]. Since amplitudes and phases have different dimensions, the search space would be large and PSO algorithm performance decreases significantly. A particle swarm optimization with passive congregation (PSOPC) mixed with least squares estimator is presented in [14]. However, PSOPC has more operators compared to simple PSO. Thereby, number of tuned factors and also computational burden are increased.

The paper presents an adaptive particle swarm optimization (APSO) to estimate the phases of harmonics. Amplitudes estimation is carried out using linear least squares. This approach is implemented in time domain and it is robust against DC offset. Different test cases are applied to evaluate the performance of presented method. In all studies, parameters used in the method are set to be fixed. The simulation results in MATLAB show that both the speed of dynamic tracking and estimation accuracy are fairly high. Furthermore, numeric indices are applied to demonstrate the improved performance of the proposed method in comparison with conventional discrete Fourier transform.

II. Proposed algorithm

Voltage and current signals in power systems consist of combination of fundamental frequency and harmonic components. Also, a decaying DC component can be added to the signal model. Generally assumed waveform structure is based on [2, 10] and [13]:

$$Z(t)=\sum_{n=1}^{N}A_n\sin(\omega_n t+\varphi_n)+A_{DC}\exp(-\alpha_{DC}t) \\ +k_s rand(t) \tag{1}$$

where $\omega_n=n2\pi f_0$ and $Z(t)$ is the measured signal; A_n Amplitude of the nth harmonic; ϕ_n the phase of nth harmonic; N the total number of harmonics; f_0 the fundamental frequency, k_s the factor of noise and $A_{DC}\exp(-\alpha_{DC}t)$ is the decaying dc component.

The discrete time version of Eq. (1) can be represented as:

$$Z(k)=\sum_{n=1}^{N}A_n\sin(\omega_n kT_s+\varphi_n)+A_{DC}\exp(-\alpha_{DC}kT_s) \\ +k_s rand(k) \tag{2}$$

Where, T_s is sampling period. DC component can be approximated using first two terms of Taylor series as:

$$A_{DC}\exp(-\alpha_{DC}t)=A_{DC}-A_{DC}\alpha_{DC}kT_s \tag{3}$$

Obviously, phases of sinusoids are the source of nonlinearity in the waveform structure. That is why hybrid methods are used to decouple the problem into linear and nonlinear parts [13, 14] and [18]. In proposed algorithm in this paper, phases are estimated using adaptive PSO. Thereby, the phase estimation problem is extracting a nonlinear relationship applying APSO. This relationship describes the mapping between phases and measured value. Squares of error between estimated and original waveforms are taken as index for evaluating objective function of APSO. The phases extracted by APSO are inserted to LS algorithm to estimate the amplitudes. In subsection 2.1 the PSO algorithm is explained in more details.

A. The principles of PSO Algorithm

Intelligent systems have excellent performance in design of algorithmic models to solve complex problems. One category of the intelligent systems is swarm intelligence. PSO is a swarm intelligence based algorithm invented by Kennedy and Eberhart [19-22]. Its initial intent is to simulate the swarm behavior of birds within a flock to construct a stochastic optimization algorithm. A swarm can be defined as interacting individuals representing possible solutions that emulate the success of other individuals. Each individual within a swarm interact to others to obtain a global optimum in a more efficient performance than one single individual could [23]. In PSO, individuals referred to as particles, are updated to produce a better solution. Each particle in the swarm pursue its best (pbest) and the best value that is tracked by the particle swarm optimizer i.e. global best (gbest). Tracking of gbest is an information sharing mechanism to give out the information of overall best particle to other particles. PSO is an iterative method with a simple formulation. Particles are updated in the following procedure. Let us assume the *N* particles at the *k*th iteration are represented as:

$$X_n^k=(x_1^k,\ldots,x_N^k) \tag{4}$$

Where, $X_n^k\in[l_n,u_n]$, l_n and u_n are the lower and upper bound for the nth particle respectively. In the first iteration the values of particles are randomly selected. The velocity vector at the same iteration is represented by $V_n^k=(v_1^k,\ldots,v_N^k)$, which each particle is bounded by a maximum velocity $V_{\max-n}^k$ and a minimum velocity $V_{\min-n}^k$ to control the likelihood of particles leaving the search space for examining more solutions. The objective function J is given for PSO. In this paper, the objective function J is calculated in each iteration as follow:

$$J(k)=[X\_est(k)-X\_mea(k)]^2 \tag{5}$$

Where X_est and X_mea are estimated and measured values for signal X respectively. Then using the objective function value, position of each particle in the iteration k is updated by following equations:

$$V_n^{k+1} = \omega V_n^k + C_1(pbest_n^k - X_n^k) + C_2(gbest^k - X_n^k) \quad (6)$$

$$X_n^{k+1} = X_n^k + V_n^{k+1} \quad (7)$$

Where, $pbest_n^k$ is the best previous position of nth particle; $gbest$ the best position among all the particles; r_1, r_2 the random variables in the range of (0,1); c_1, c_2 the positive acceleration constants and ω is the inertia weight.

In this paper an adaptive inertia weight, thereby an adaptive particle swarm optimization (APSO) algorithm is used. A larger inertia weight facilitates global exploration and a smaller inertia weight tends to facilitate local exploration [17]. Therefore, adaptive inertia weight makes a balance between global and local exploration abilities. Hence, less number of iterations is needed for algorithm convergence. In each iteration step, the hybrid algorithm applies APSO for phase estimation and then calculates amplitude of harmonics using LS. Finally, with the values of the phases and amplitudes, the fitness value of each particle is calculated by Eq. (5) and then each particle position is updated by Eq. (6) and (7). The process repeats until an acceptable convergence is attained. Fig. 1 represents a flowchart for the formulation of PSOs.

B. Amplitude estimation using LS

The basic concept of least squares algorithm is introduced in [24-26]. The discrete linear model of waveform in Eq. (2) can be rewritten as:

$$Z(k) = H(k)\theta(k) + \varepsilon(k) \quad (8)$$

Where $Z(k)$ is the kth sample of the measured signal; $H(k)$ is the system structure matrix; $\theta(k)$ is the unknown parameters matrix (Amplitudes) to be estimated and $\varepsilon(k)$ is unknown noise. Applying measurements $Z(k)$, the LS estimation of θ i.e. θ_e can be extracted by minimizing following function:

$$J(\theta_e(k)) = [Z(k) - H(k)\theta_e(k)]^T [Z(k) - H(k)\theta_e(k)] \quad (9)$$

Estimating the phases by APSO, structure matrix is obtained and function $J(\theta_e(k))$ is minimized that results in:

$$\theta_e(k) = [H^T(k)H(k)]^{-1} H(k)X(k) \quad (10)$$

the structure matrix $H(k)$ is assumed:

$$H = \begin{bmatrix} \sin(\omega_1 t_1 + \varphi_1) & \sin(\omega_2 t_1 + \varphi_2) & \dots & \sin(\omega_N t_1 + \varphi_N) \\ \sin(\omega_1 t_2 + \varphi_1) & \sin(\omega_2 t_2 + \varphi_2) & \dots & \sin(\omega_N t_2 + \varphi_N) \\ . & . & & . \\ . & . & \dots & . \\ . & . & & . \\ \sin(\omega_1 t_k + \varphi_1) & \sin(\omega_2 t_k + \varphi_2) & \dots & \sin(\omega_N t_k + \varphi_N) \end{bmatrix} \quad (11)$$

The output of *LS* is the estimated amplitude vector as follow:

$$\theta(k) = [A_1(k) \;\; A_2(k) \; \dots \; A_N(k) \;\; A_{DC} \;\; A_{DC}\alpha_{DC}]^T \quad (12)$$

The objective function of the APSO is obtained using (3). The estimation process until reaching an acceptable solution continues.

The APSO-LS algorithm can be explained by following steps:

1) Initialize swarm of PSO.
2) Load the test signal.
3) For each individual, extract the H(k) matrix from (11).
4) Estimate the harmonic amplitudes according to each individual using (10).
5) Construct the waveform corresponding to each individual using estimated parameters.
6) Evaluate the performance of each individual using (3) to gbest and pbest appointment.
7) Update the swarm using (6) and (7).
8) Repeat steps two to seven until final convergence.

III. Simulation Results

Several papers have been applied on the same power system signal which is used in this paper. The test signal is a combination of a series of sinusoidal components. Each component has its own amplitude, phase and frequency.

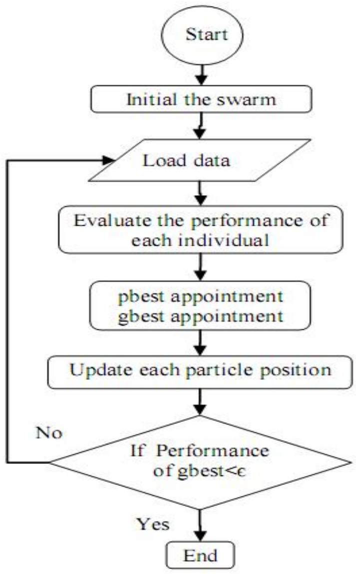

Fig. 1. Basic flowchart showing the sequence of operations in a PSO

The distorted waveform is represented by [2, 10]:

$$X(t) = 1.5\sin(\omega t + 80°) + 0.5\sin(3\omega t + 60°) + 0.2\sin(5\omega t + 45°) + 0.15\sin(7\omega t - 36°) + 0.1\sin(11\omega t + 30°) + 0.5\exp(-5t) + k_s\, rand(t) \tag{13}$$

The test signal is a distorted waveform sampled from the terminal of industrial load comprising power electronic converters and arc furnaces [2]. As can be seen, five harmonics are considered in the test signal. The additive Gaussian noise has a zero mean and variance of unity. Factor k_s represent the amplitude of the noise whose value is chosen 0.05 in this study. This section shows the performance of the APSO-LS method. To investigate the performance of the proposed approach several tests are performed. Different types of this simulation tests are applied as follow:

1) Static signal test
2) Dynamic (time varying) signal test
3) Test the frequency drift effect on signal
4) Test the faulted power system

To compare the performance of the proposed method with conventional DFT, the following indices are applied:

a) Mean Square Error (MSE) of the estimated signal to show the estimation precision.

b) Estimated waveform error variance, which can be interpreted as estimation robustness against random noise.

A. Static signal test

The static signal test is implemented using the discrete time version of distorted signal represented in Eq. (13). A simple adaptive inertia weight ω is used for PSO. This parameter can be made by means of mathematics, the description is:

$$\omega = (\omega_{\max} - (\omega_{\max} - \omega_{\min}) / iter) * k \tag{14}$$

The inertia weight is bounded by maximum value $\omega_{\max}$ and minimum value $\omega_{\min}$. *iter* is the number of iterations for obtaining an acceptable convergence and k is the current iteration times. The values of $\omega_{\max}$ and $\omega_{\min}$ are chosen as 0.78 and 0.16 respectively. Large inertia weights cause larger exploration of the search space, while smaller inertia weights focus the search on a smaller region [23]. Acceleration constants c_1 and c_2 control the movement of particle in each iteration. In this study c_1 and c_2 are set to be 2.7 and 0.4 respectively. Nominal frequency of power system is 50 Hz and a sampling frequency 2.3 kHz is used for numerical computation. The number of parameters to be estimated is twelve. The five amplitudes and five phases for the assumed harmonics and two terms of Taylor series of DC component are estimated in each iteration. Phases are estimated using APSO and others with LS method. Figs. 2 and 3 show tracking results of fundamental and the 7th harmonic parameters with APSO-LS. These results are extracted for a test signal corrupted with random noise and decaying DC component. This method begins tracking of the amplitudes and phases of harmonics in less than one cycle. As can be seen an acceptable value for amplitudes is obtained after about 0.65 cycles (13ms). Convergence time for phases is about 0.85 cycles (17ms). APSO-LS approach shows almost the same tracking behavior in estimating the amplitudes and phases of other harmonics. The accuracy of this approach is observed from simulation results and specified points in figures. Using estimated parameters, the estimated waveform is reconstructed. For evaluating the overall tracking quality, estimated signal and original test signal are compared. Fig. 4 represents results of this comparison. Also overall tracking error is represented in Fig. 5. To compare the APSO-LS method with DFT, numerical performance indices, as were described earlier, are calculated in table. 1. Table 1 shows that APSO-LS does the estimation with fewer errors and has less variation. As it was mentioned earlier, this shows the better noise rejection of APSO-LS method.

B. Dynamic (time varying) signal test

Electrical waveforms magnitude in a practical power system is always time varying. The shape of amplitudes depends on load that produces the disturbance. In this paper, dynamic signal with the same harmonics considered in the static signal is assumed. However the DC component is not eliminated, the APSO-LS provides an exact dynamic estimation of the harmonic parameters. To demonstrate the performance of APSO-LS method in abrupt changes tracking, following model is provided:

$$Z(t) = [1.5 + a_1(t)]\sin(\omega t + 80°) + [0.5 + a_3(t)]\sin(3\omega t + [0.2 + a_5(t)]\sin(5\omega t + 45°) + 0.15\sin(7\omega t - 36°) + 0.1\sin(11\omega t + 30°) + 0.5\exp(-5t) + k_s\, rand(t) \tag{15}$$

where

$$a_1 = 0.15\sin 2\pi f_1 t + 0.05\sin 2\pi f_5 t,$$
$$a_3 = 0.05\sin 2\pi f_3 t + 0.02\sin 2\pi f_5 t,$$
$$a_5 = 0.025\sin 2\pi f_1 t + 0.005\sin 2\pi f_5 t$$

and $f_1 = 1Hz, f_3 = 3Hz, f_5 = 6Hz$.

k_s is set to be 0.05 . Figs. 6 and 7 show the estimation of the 3rd and the 5th harmonic parameters respectively. Estimated and measured signal waveforms are shown in Fig. 8. Characteristics of APSO are the same as in static signal. It causes the simplicity of use of adaptive parameters in proposed method. In spite of existence of DC component and random noise, this algorithm can track abrupt changes of signal.

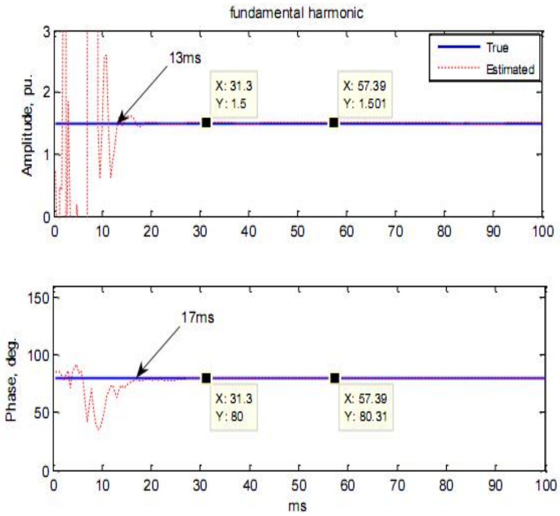

Fig. 2. Tracking the fundamental harmonic's parameters

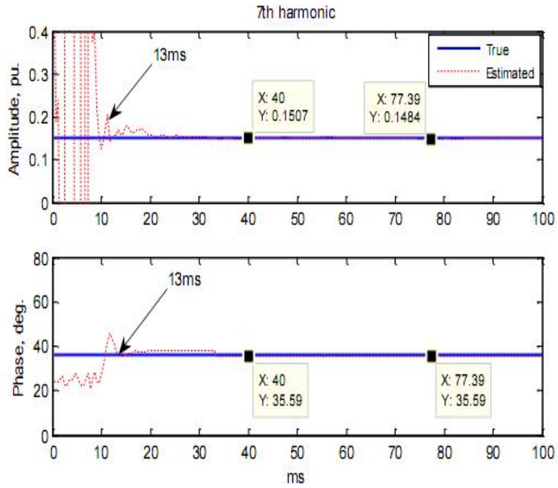

Fig. 3. Tracking the 7th harmonic's parameters.

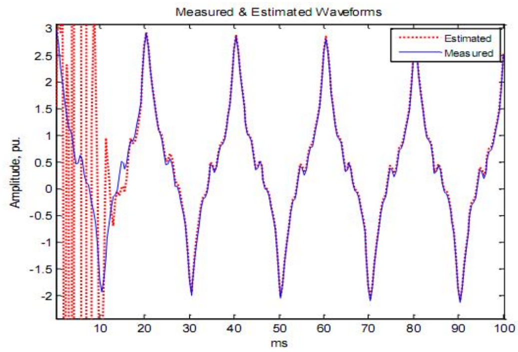

Fig. 4. Measured and estimated waveforms.

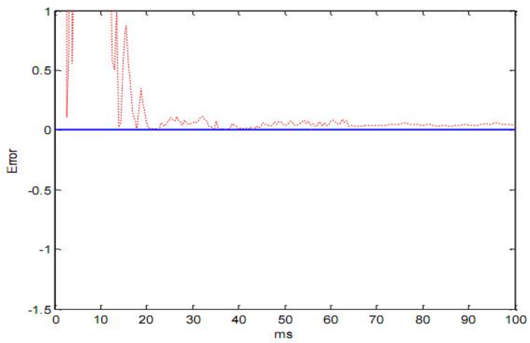

Fig. 5. Error of estimation.

TABLE I

MSE AND VARIANCE INDICES OF PROPOSED METHOD COMPARED DFT (STATIC SIGNAL ESTIMATION).

	APSO-LS	DFT
MSE	$44*10^{-6}$	0.0122
Variance	$157*10^{-6}$	0.0244

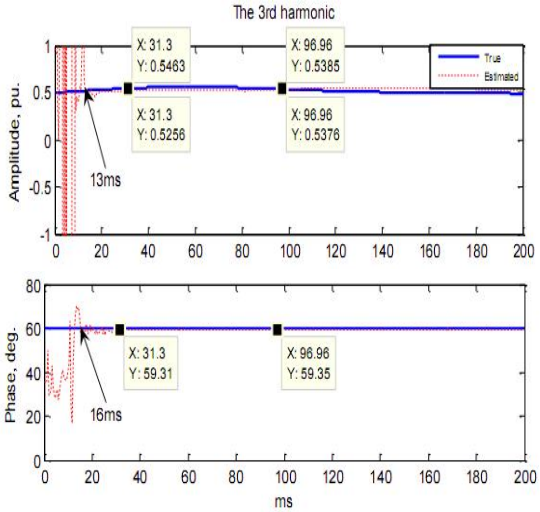

Fig. 6. Tracking the 3rd harmonic's parameters.

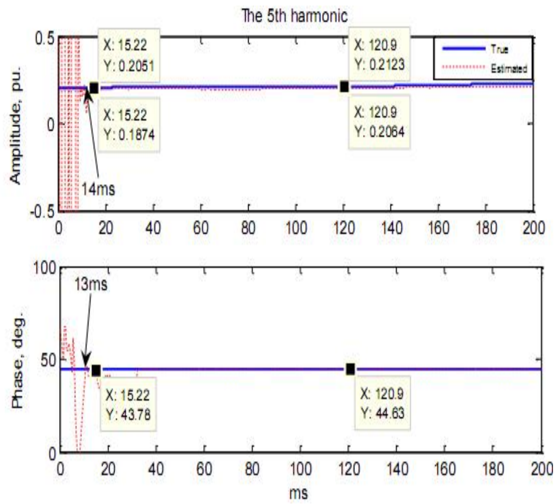

Fig. 7. Tracking the 5th harmonic's parameters.

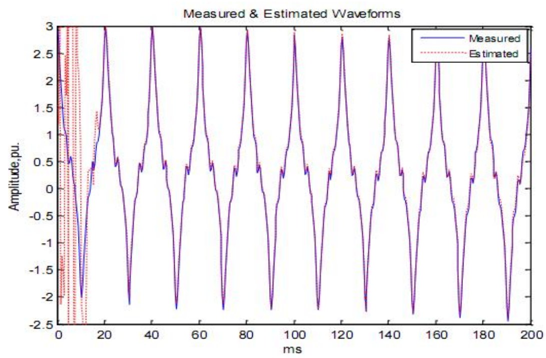

Fig. 8. Measured and estimated waveforms.

From the Figs. 6 and 7, it can be seen that APSO-LS can converge to an acceptable value in less than one cycle. It also converges to final values with high accuracy. Fig. 9 shows the error of this tracking. The contents of table 2 prove the precision of the proposed algorithm in comparison with DFT. This table indicates better performance of APSO-LS in rejecting the noise.

C. Effects of frequency drift on harmonic estimation

Frequency drift widely exists in power systems. Estimating the harmonic parameters in the presence of frequency drift is a challenging problem in harmonic estimation. In this study the effects of frequency drift on the estimation procedure of proposed algorithm is tested. A large value of frequency drift $\Delta f = -1 Hz$ is set at the beginning of the second cycle. System frequency is restored to reference value after 33 ms. Since the frequencies of harmonics are the multiples of the fundamental frequency, harmonic drift is expanded to include higher harmonics. Results of amplitudes and phases estimation for fundamental and the 11th harmonic parameters are represented in Figs. 10 and 11. However this results are obtained in presence of random noise $(k_s = 0.05)$ and DC component, the estimated values are quite close to their reference values. As can be seen, phase estimation by APSO does not have considerable variation. The reason of this behavior is that all the individuals are pulled toward optimum point of phases before the frequency drift be observed by APSO-LS. Figs. 12 and 13 show the overall tracking quality of APSO-LS. APSO-LS tracks the parameters without interval if small frequency drift of 0.1 Hz, or less is exerted to the signal. Computed performance indices are represented in table3.

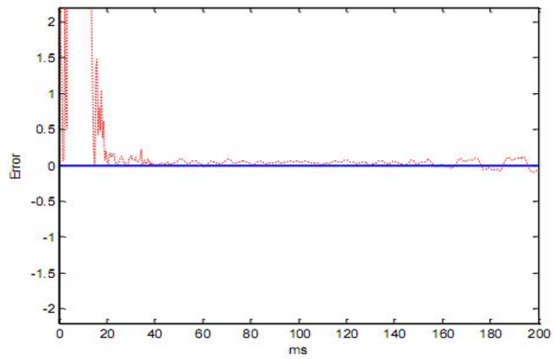

Fig. 9. Error of estimation.

TABLE II
MSE AND VARIANCE INDICES OF PROPOSED METHOD COMPARED TO DFT (DYNAMIC SIGNAL ESTIMATION).

	APSO-LS	DFT
MSE	$43*10^{-5}$	0.0202
Variance	$98*10^{-5}$	0.0286

D. Test the faulted power system

The proposed method is used to estimate the correct values of amplitudes and phases of harmonic components in a faulty power system. A single-line-to-ground fault on the A-phase of a transmission line is applied for this purpose. The fault occurs at the beginning of the second cycle and the post fault waveform contains a considerable decaying dc component. A good harmonic estimation algorithm should yield precise estimates even for distorted and noisy signal and track abrupt changes in the parameters. To demonstrate the performance of APSO-LS in abrupt change tracking, change of test signal is boosted. The proposed algorithm show a good consistency with different condition which are exerted to the signal test. Hence, a set of constant parameters are used for APSO-LS in all test cases.

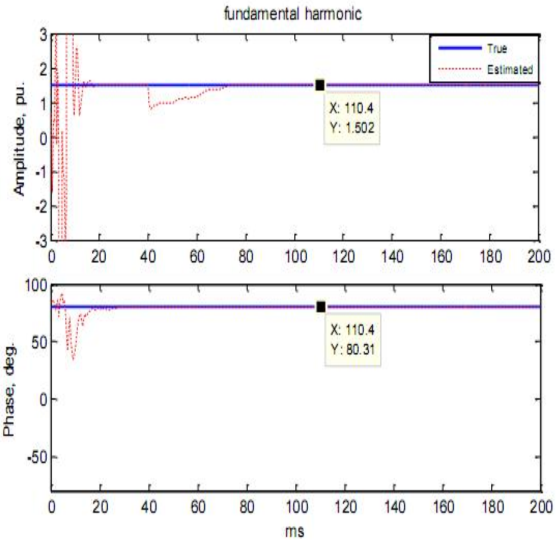

Fig. 10. Tracking of fundamental harmonic's parameters.

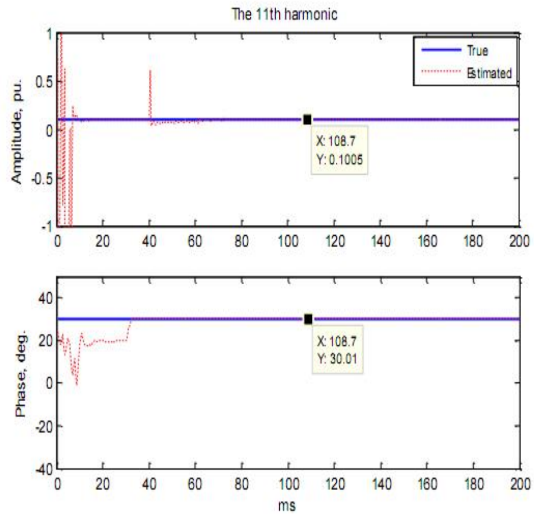

Fig. 11. Tracking of 11th harmonic's parameters.

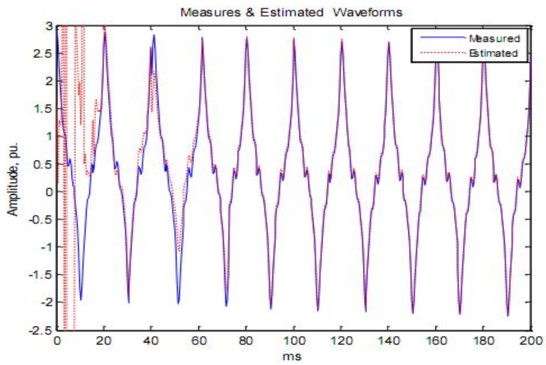

Fig. 12. Measured and estimated waveforms.

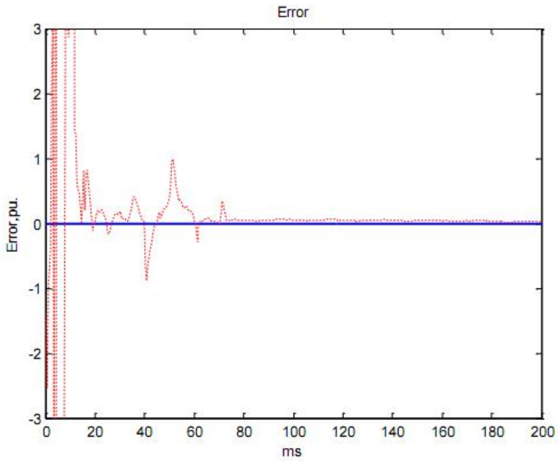

Fig. 13. Error of estimation.

TABLE III
MSE AND VARIANCE INDICES OF PROPOSED METHOD COMPARED TO DFT (SIGNAL ESTIMATION IN FREQUENCY DRIFT).

	APSO-LS	DFT
MSE	$38*10^{-6}$	0.0128
Variance	$102*10^{-6}$	0.0227

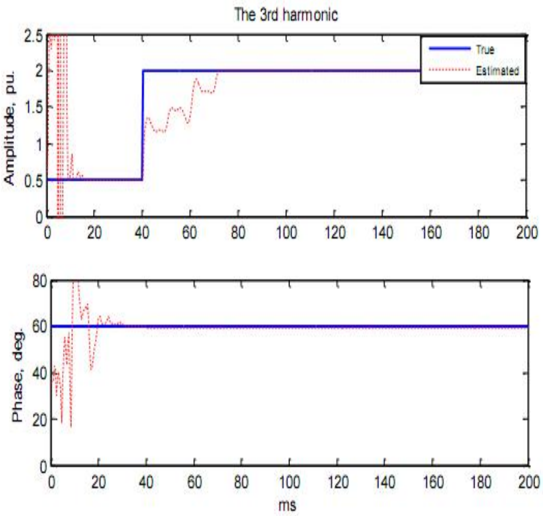

Fig. 14. Tracking of 3rd harmonic's parameters.

Because tracking behavior for all harmonic components is almost the same, only tracking results of the 3rd and the 5th harmonic parameters are shown in Figs. 14 and 15. These results are obtained in presence of random noise. Fig. 16 shows the estimated and measured signal together. Successful implementation of the proposed method is observed from overall tracking error represented in Fig. 17. The results shown in table 4 clearly indicate that APSO-LS obtain smaller error than DFT, which means that the proposed algorithm achieves an improved estimation accuracy in comparison with DFT.

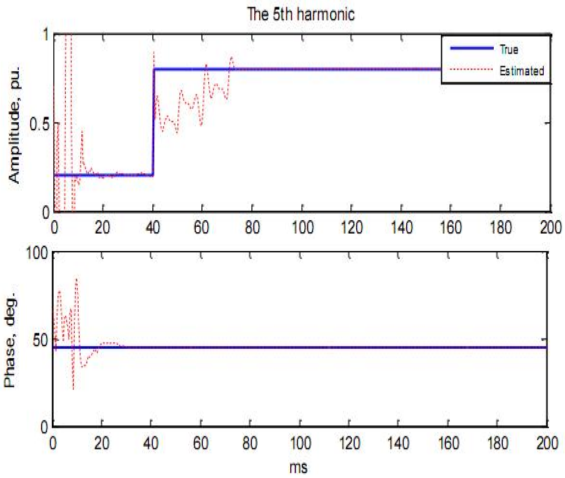

Fig. 15. Tracking of 5th harmonic's parameters.

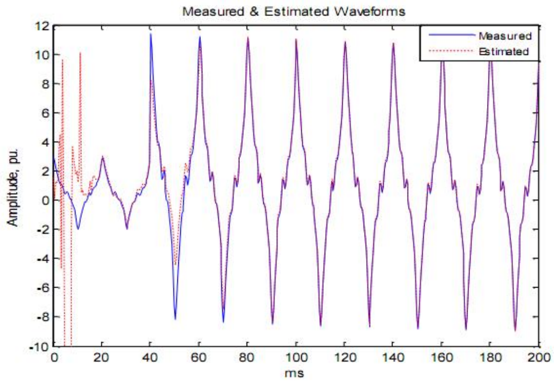

Fig. 16. Measured and estimated waveforms.

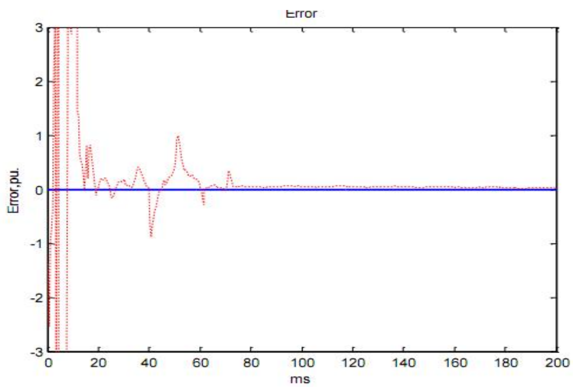

Fig. 17. Error of estimation.

TABLE IV
MSE AND VARIANCE INDICES OF PROPOSED METHOD COMPARED TO DFT (SIGNAL ESTIMATION IN FAULTED SYSTEM).

	APSO-LS	DFT
MSE	$46*10^{-6}$	0.0131
Variance	$143*10^{-6}$	0.0258

IV. CONCLUSION

In this paper a new approach for estimating amplitudes and phases of the harmonics in a distorted waveform is proposed. This hybrid approach uses combination of adaptive PSO and LS estimator. In each iteration of the estimation algorithm, APSO is applied for estimating the phases. Using extracted phases, amplitude vector is estimated by LS. Furthermore, this method can track the DC component magnitude in different conditions, thereby; the proposed technique is immune to transient DC component and random noise, even in time-varying signal tracking. The advantages of APSO-LS technique are high convergence speed and precise estimation of harmonic parameters. The parameters converge to the true value in less than one cycle in all the test cases. Using a fast processor, the algorithm can be used in online signal tracking. Moreover, APSO-LS is enable to detect the harmonic parameters in other types of signals such as communication signals and other encrypted signals. Obtained results by MATLAB codes indicate the accuracy and high-performance of APSO-LS in different case studies.

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