Measurement 45 (2012) 1436–1454

Contents lists available at SciVerse ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

Estimation of time-varying power quality indices using a computationally efficient algorithm

P.K. Dash *, Milan Biswal, Krishnanand K.R.

Siksha O Anusandhan University, Bhubaneswar, India

ARTICLE INFO

Article history:
Received 23 July 2011
Received in revised form 16 February 2012
Accepted 21 March 2012
Available online 30 March 2012

Keywords:
Power quality indices
Harmonics
Power measurement
Sequence components

ABSTRACT

In this paper a new recursive adaptive filter based on a fast Gauss–Newton method has been proposed for the estimation of power quality (PQ) indices for time-varying voltage and current signals in an electric power system. The presented algorithm is based on the minimization of a weighted forgetting factor based error cost function by the use of Recursive Gauss–Newton method. Further a Hessian matrix approximation is used to produce a fast recursive algorithm, which is immune to random noise, waveform distortion and increases the speed of convergence and accuracy. The algorithm models the typical time-varying signal and the accompanied distortions due to harmonics and random noise in a manner that will be suitable for real-time PQ indices estimation. Further, the forgetting factor is tuned in accordance with signal error covariance to provide improved performance. Also power system frequency variations are estimated and correction factors are derived. The effects of sub harmonics, and interharmonics in the signal have been considered while estimating the various PQ indices.

1. Introduction

Estimation of PQ indices has assumed increased importance in recent years due to the development of several numerical algorithms and hardware architectures to monitor power quality in distribution networks. Further with increased interest in electric power network restructuring under deregulation and the use of distributed generators in power distribution networks in a microgrid environment, PQ indices estimation is essential for fixing the market price of electricity. Also the power quality studies have assumed great importance for renewable energy systems like wind, solar and fuel cells where harmonics are generated in abundance.

There are a variety of measurement techniques available for estimation of PQ indices and also dedicated hardware devices are used to monitor power quality. For power quality estimation, the requirement includes a fast and reliable algorithm for determining the electric power signal parameters that will be useful in a real-time environment. Amongst the commonly used methods, the Fast Fourier Transform (FFT) suffers from leakage and picket fence effects and without windowing it introduces error in measurement of harmonics in the presence of noise.

Other techniques include adalines and neural network [1,2], recursive Continuous Wavelet Transform (CWT) for PQ monitoring [3], least squares [4–6], Recursive Newton Type Algorithm [7–9], Gauss–Newton methods [10,11], Kalman, and unscented Kalman Filter [12–15], etc. Also recently several new techniques like iterative loop approach [16], vector transformations [17], on-line methods [18,19] have been presented for estimating power signal parameters under time varying and distorted conditions. The Extended Kalman Filter [12] used to extract the amplitude, phase and frequency of a power signal suffers from a lack of knowledge about the statistical properties of the power signal and the accurate knowledge of the covariance accompanied by significant computational overhead.

Amongst all these methods the adaline presents the least amount of computational overhead and other methods

* Corresponding author. Fax: +91 674 2725312.
E-mail address: pkdash.india@gmail.com (P.K. Dash).

0263-2241/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.measurement.2012.03.018

like Newton and Gauss–Newton methods become computationally involved with increased order of harmonics in the signal and high sampling rate. The recursive Newton method [9] has been presented to compute the signal frequency without estimating the amplitude and phase of the signal. On the other hand, the recursive Gauss–Newton algorithm [10] estimates the amplitude and phase of the sinusoids in the presence of noise with the assumption that the fundamental and harmonic signal frequencies are known. Thus an overall algorithm is required to estimate all the voltage and current signal parameters like the amplitude, phase of the fundamental and harmonics, fundamental frequency, and the decaying *dc* components if any.

This paper, therefore, presents a computationally less involved Recursive Gauss–Newton Algorithm to estimate the various signal parameters that will be ultimately used for PQ indices computation. Using approximations, a new fast Gauss–Newton algorithm is considered in this paper to estimate fundamental and harmonic phasors along with decaying *dc* components if any which are required to evaluate the power quality indices. Further the algorithm can also take into account the time varying nature of the power signals like the sudden changes in amplitude, phase angles, and frequency of the fundamental and harmonic components and results in fast convergence to true values with significant accuracy. Using extensive simulations, the superiority of this algorithm over the LMS filtering technique has been verified. The paper is organized in five sections: After introduction in Sections 1 and 2 presents a detailed signal model that includes decaying *dc*, fundamental, and harmonics embedded in noise. In this section also the fast Gauss–Newton algorithm is presented for the signal model described in the beginning. In Section 3, the computation of actual frequency drift is presented and various correction factors are presented to accurately compute the parameters of the time varying 3-phase voltage or current signals. After computing the various voltage and current parameters, estimation of power quality indices is presented in Section 4. The various sequence voltages, currents, and powers are presented in Sections 5 and 6 considers several test cases and provides results which exhibit robustness of accuracy and convergence in the presence of noise. Concluding remarks are given in Section 7.

2. Power signal model and fast Gauss–Newton algorithm

The observed power, voltage or current signal is assumed to comprise a decaying *dc* component, fundamental and harmonics of order N and is represented by,

$$y(t) = s(t) + v(t) \tag{1}$$

where $y(t)$ is the time-varying voltage or current signal at time t, $v(t)$ is the random noise and $s(t)$ is the signal model given by,

$$s(t) = a_{dc}e^{-\alpha_{dc}t} + \sum_{n=1}^{N}(a_n \cos n\omega_0 t + b_n \sin n\omega_0 t) \tag{2}$$

where a_n and b_n are the direct and quadrature components of the nth order harmonic, a_{dc} and α_{dc} are the magnitude and time constant of the decaying *dc* component.

The discrete version of the above model is obtained after expanding the decaying *dc* term as

$$s(t) = a_{dc} - a_{dc}\alpha k + \sum_{n=1}^{N}(a_n \cos n\omega + b_n \sin n\omega) \tag{3}$$

where $\alpha = \alpha_{dc}T_s$, $\omega = \omega_0 T_s$ and T_s is the sampling interval and is equal to $1/f_s$;f_s is the sampling frequency.

For PQ indices estimation, it is necessary to evaluate amplitude, phase and frequency of the voltage and current signals and in this paper, the Gauss–Newton Algorithm is outlined below. Here the conventional Gauss–Newton algorithm is approximated to provide a faster evaluation of PQ indices. For the evaluation of a_n, b_n and ω, a weighted error cost function of the form,

$$\varepsilon(k) = \sum_{i=0}^{k}\lambda^{k-i}[y(k) - a_n(k-1)\cos\omega(k-1) - b_n(k-1) \times \sin\omega(k-1) - a_{dc}\{1-\alpha(k-1)\}] \tag{4}$$

is used.

Where λ is the forgetting factor that controls the quality of estimation in terms of accuracy and speed of convergence. The error cost function is minimized using the Gauss–Newton Algorithm (GNA) to yield the power signal parameters a_n, b_n, ω, a_{dc}, and α_{dc}. The GNA is outlined in the following steps:

Denoting the estimated vector as,

$$\hat{\theta}_n(i) = [a_{dc}(i)\alpha_{dc}\hat{a}_n(i)\hat{b}_n(i)\hat{\omega}_e(i)] \tag{5}$$

And the parameter vector is obtained using the Gauss–Newton Algorithm as,

$$\theta_n(k) = \theta_n(k-1) + H^{-1}(k)\psi(k)\cdot e(k) \tag{6}$$

where H is the Hessian matrix, and ψ is the gradient vector defined in Eqs. (8) and (10), respectively.

$$H(k) = \lambda H(k-1) + \psi(k)\psi^T(k) \tag{7}$$

where $\psi(k)$ and $H(k)$ are obtained as,

$$H(k) = \sum_{i=0}^{k}\lambda^{k-i}\psi(i)\cdot\psi^T(i) \tag{8}$$

For updating the Hessian matrix, $H^{-1}(k)$, the matrix inversion lemma is used as,

$$H^{-1}(k) = \frac{1}{\lambda}\left[H^{-1}(k-1) - \frac{H^{-1}(k-1)\psi(k)\psi^T(k)H^{-1}(k-1)}{\lambda + \psi^T(k)H^{-1}(k-1)\psi(k)}\right] \tag{9}$$

Since the harmonic frequencies are integer multiples of the fundamental frequency, the above model can be used to estimate in the first step, the fundamental, harmonics and *dc* components and in the next step, the frequency will be estimated from the fundamental component output. Thus the reformulated $\frac{\partial\psi}{\partial\theta_n}$ vector becomes,