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The Adaptive Signal Processing Scheme for Power Quality Conditioning Applications Based on Active Noise Control (ANC)

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Introduction

Adaptive filter theory has been increasingly utilized in various applications, such as the active noise cancellation, channel estimation and equalization and the acoustic echo cancellation [1, 2]. The gradient descent (GD) algorithm and the least mean square (LMS) are the most popular training algorithms for the adaptive filters. In the previous literatures [3–5], the fixed step–size LMS was applied to reach a compromise between the convergence rate and the steady–state mean square error (MSE) of the LMS training algorithm. It is well known that higher step–size improves the convergence rate and lower step–size decreases the MSE. In [6], two new variable step–size (VSS) normalized LMS (NLMS) and the affine projection adaptive (APA) were presented, and the optimal selection of the step–size for fast convergence rate and low steady–state MSE was derived. In [7], the generic adaptive filter based on the weighted Wiener–Hopf equation was proposed and the transient analysis of different adaptive filter algorithms was discussed. In [8], a unified framework for adaptive filter algorithms with variable step–size was presented, which covers both the classical and modern adaptive filter algorithms, such as block normalized LMS (BNLMS) and normalized data reusing LMS (NDRLMS) adaptive filter algorithms, with variable step–size NLMS and VSS affine projection algorithms as special cases.

In [9–16], the adaptive linear neural network (ADALINE) was utilized in electrical engineering applications, which in essence, belongs to adaptive noise control (ANC) system. In [9], the ADALINE–based control of capacitor supported DVR for power quality improvement in distribution system was presented. And a recursive notch filter was applied to generate reference current for the single–phase active power filter (APF) by using the ADALINE–based neural filtering technique in [10]. In [11], a new identification scheme of grid voltages and load currents was proposed for APFs, also based on the ADALINE networks. In order to overcome the shortcomings of the conventional ADALINE networks, a modified ADALINE structure was introduced in [12], which is capable of dealing with off–nominal frequency conditions. The presented ADALINE structure, named S–ADALINE, is able to synchronize itself with the system signals using an efficient fundamental frequency deviation estimation algorithm, which was confirmed by laboratory tests. In [13], a synchronous rotating reference frame ADALINE (SADALINE) was proposed to simplify computational complexity, and it was applied to the three–phase active power filter for verification. It was reported that the SADALINE shows overwhelming advantages over the stationary frame solutions in terms of simplicity, robustness and easy of implementations.

In [14], a novel hybrid approach for power system harmonic estimation was proposed using least square (LS) algorithm, which in essence, belongs to the aforementioned ADALINE scheme. Nevertheless, the discrete domain modeling and parameter selection guidelines for optimal tuning the performance were not discussed. In [15], the ADALINE was applied to the single phase auto–reclosure scheme for the EHV power transmission lines, and the simulation results confirmed the improved reliability and efficiency of the 400kV transmission line by using the ADALINE scheme. In [16], an improvement of the intelligent sliding model control (SMC) was achieved by using the ADALINE, based on the fractional calculus and the tuning scheme of the ADALINE was revised according to the rules of fractional order differ–integration.

The accurate estimation of electric signals, i.e., the grid voltages, the nonlinear load currents is vital for the grid–connected converters for the power quality conditioning applications. However, a detailed, systematical theoretical derivation, criterion for step–size parameter selection of the ADALINE scheme was not presented in the available literatures [9–16]. This paper aims to cover this gap and present the theoretical background of the ADALINE for the power quality conditioning applications [13, 17–19]. The nonlinear currents decomposition into fundamental active, reactive and harmonic components is utilized as benchmark problem for the illustration using the adaptive estimation scheme.

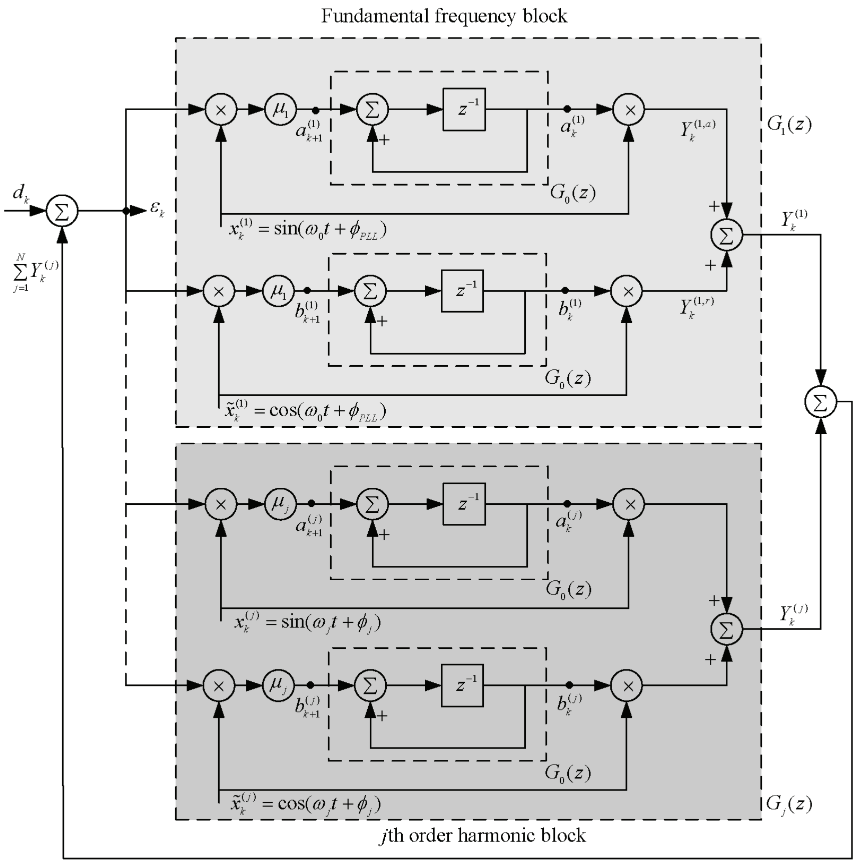


Fig. 1. The discrete–time representation of the adaptive signal processing scheme based on active noise control

Mathematical derivation of the ANC for power quality conditioning applications

This section presents the adaptive signal decomposition scheme using adaptive noise control (ANC), which is also known as adaptive linear neural network (ADALINE) [9–16, 20]. An arbitrary signal $Y(t_k)$ can be expressed by the Fourier series expansion as:

$$\begin{aligned} Y(t_k) &= \sum_{n=0,1,2,3,\cdots}^{N} A_n \sin(n\omega_0 t_k + \varphi_n) + n(t_k) = \\ &= \sum_{n=0,1,2,3,\cdots}^{N} (a_n \sin 2\pi n f_0 t_k + b_n \cos 2\pi n f_0 t_k) + n(t_k), \end{aligned} \tag{1}$$

where A_n and φ_n are correspondingly the amplitude and phase angle of the nth order harmonic component, and $n(t_k)$ represents higher order components and random noise. Followed by the definition in [1–2], the pattern vector X_k and weight vector W_k of ADALINE can be defined as:

$$\tilde{X}_k = [1, \sin\omega_0 t_k, \cos\omega_0 t_k, \cdots, \sin N\omega_0 t_k, \cos N\omega_0 t_k\ ]^T, \tag{2}$$

$$\tilde{W}_k = [b_0^k, a_1^k, b_1^k, a_2^k, b_2^k, ..., a_N^k, b_N^k]^T. \tag{3}$$

However, when the ADALINE estimation algorithm is applied for nonlinear load current decomposition, it can be observed from the equations (1)–(3) that the fundamental frequency active and reactive component cannot be directly estimated. In order to cope with this shortcoming of the conventional ADALINE [9–16], the fundamental frequency component of $Y(t_k)$ can be rewritten as:

$$\begin{aligned} Y_1(t_k) &= A_1 \sin(\omega_0 t_k + \varphi_1) = \\ &= A_1 \sin(\omega_0 t_k + \varphi_{PLL} + \varphi_1 - \varphi_{PLL}) = \\ &= A_1 \sin(\omega_0 t_k + \varphi_{PLL}) \cos(\varphi_1 - \varphi_{PLL}) = \\ &\quad + A_1 \cos(\omega_0 t_k + \varphi_{PLL}) \sin(\varphi_1 - \varphi_{PLL}), \end{aligned} \tag{4}$$

where φ_{PLL} represents the initial phase angle of the fundamental frequency grid voltage, and $\omega_0 t_k + \varphi_{PLL}$ represents the phase angle of the fundamental frequency grid voltage, which are obtained from the phase–locked–loop (PLL). It should be noted that a phase–locked–loop (PLL) is utilized to generate the reference phase angle for the grid–connected converters, which is synchronized with the fundamental component of grid voltage. One may refer to a detailed description of the PLL schemes in [19, 24].

Referring to equation (4), we can redefine the weight vector for the fundamental component load current $Y_1(t_k)$, as follows:

$$a_1^k = A_1 \cos(\varphi_1 - \varphi_{PLL}), \tag{5}$$

$$b_1^k = A_1 \sin(\varphi_1 - \varphi_{PLL}). \tag{6}$$

Therefore, equations (2)–(3) can be rewritten as:

$$X_k = [1, \sin(\omega_0 t_k + \varphi_{PLL}), \cos(\omega_0 t_k + \varphi_{PLL}), \cdots, \sin N\omega_0 t_k, \cos N\omega_0 t_k \;]^T, \quad (7)$$

$$W_k = [b_0^k, a_1^k, b_1^k, a_2^k, b_2^k, ..., a_N^k, b_N^k]^T. \quad (8)$$

Supposing the fundamental grid voltage is denoted by $v_1 = V_1\sin(\omega_0 t_k + \varphi_{PLL})$, and its phase angle is extracted by the PLL and utilized as the input vector for the ADALINE, as indicated by equation (7). Then it can be deduced that after the convergence of the adaptive estimation algorithm, the weights a_1, b_1 converge to the amplitudes of the active and reactive components of load fundamental component current, which can be utilized for the reference current generation for the current–loop controller of the active power filters (APFs) [10–13]. The same principle can also be utilized for blind signal separation [21], and other grid–connected power converters applications [22–24].

Fig. 1 shows the discrete–domain representation of ADALINE estimation algorithm for nonlinear load currents decomposition. From equations (7)–(8), it shows that the initial phase angle of harmonic components φ_j of the reference signal $x_k^{(j)}$ and $\tilde{x}_k^{(j)}$ equals to zero in Fig. 1. Next, the statistical characteristics, discrete–domain analysis and selection of step–size of the ADALINE algorithm would be presented. Once again referring to Fig. 1, the square error on the pattern X_k at the kth iteration can be expressed as [9–13]:

$$\varepsilon_k = \frac{1}{2}(d_k - X_k^T W_k)^2 = \frac{1}{2}e_k^2 = \frac{1}{2}(d_k^2 - 2d_k X_k^T W_k + W_k^T X_k X_k^T W_k), \quad (9)$$

where d_k is the desired scalar output at the kth iteration. The mean–square error (MSE) ε is obtained by calculating the expectation of both sides of equation (9), as:

$$\varepsilon = E[\varepsilon_k] = \frac{1}{2}E[d_k^2] - E[d_k X_k^T]W_k, + \frac{1}{2}W_k^T E[X_k X_k^T]W_k, \quad (10)$$

where the weights are assumed to be fixed at W_k while computing the expectation. The objective of the adaptive linear neural network (ADALINE) is to find the optimal weight vector $\hat{W}_k$ that minimizes the MSE of (10). For convenience of expression, equation (10) is rewritten as:

$$\varepsilon = E[\varepsilon_k] = \frac{1}{2}E[d_k^2] - P^{\mathrm{T}}W_k + \frac{1}{2}W_k^{\mathrm{T}}\mathbf{R}W_k, \quad (11)$$

where P^{T} and $\mathbf{R}$ are defined as [13]:

$$P^T = E[d_k X_k^{\mathrm{T}}] = E[(d_k, d_k\sin(\omega_0 t_k + \varphi_{PLL}), d_k\cos(\omega_0 t_k + \varphi_{PLL}), \cdots, d_k\sin N\omega_0 t_k, d_k\cos N\omega_0 t_k \;)]. \quad (12)$$

$$\mathbf{R} = E[X_k X_k^{\mathrm{T}}] = E\begin{bmatrix} 1 & \dots & \cos N\omega_0 t_k \\ \sin(\omega_0 t_k + \varphi_{PLL}) & \dots & \sin(\omega_0 t_k + \varphi_{PLL})\cos N\omega_0 t_k \\ \dots & \dots & \dots \\ \cos N\omega_0 t_k & \dots & \cos N\omega_0 t_k \cos N\omega_0 t_k \end{bmatrix}. \quad (13)$$

It can be observed that the correlation matrix $\mathbf{R}$ is real and symmetric, and ε is a quadratic function of the weight vector. The gradient function $\nabla\varepsilon$ corresponding to the MSE function of equation (11) is:

$$\nabla\varepsilon = (\frac{\partial\varepsilon}{\partial b_0^k}, \frac{\partial\varepsilon}{\partial a_1^k}, \frac{\partial\varepsilon}{\partial b_1^k}, ..., \frac{\partial\varepsilon}{\partial a_N^k}, \frac{\partial\varepsilon}{\partial b_N^k})^T = -P + \mathbf{R}W_k, \quad (14)$$

which is a linear function of weights. The optimal set of weights, $\hat{W}_k$, can be obtained by setting $\nabla\varepsilon = 0$, which yields

$$-P + \mathbf{R}\hat{W}_k = 0. \quad (15)$$

The solution of the equation (15) is called Weiner solution or the Weiner filter [1–2]:

$$\hat{W}_k = \mathbf{R}^{-1}P, \quad (16)$$

which is exactly the solution of the Weiner–Hopf equation in matrix representation, one may refer to Refs.[1–2,13] for the detailed discussion on the mathematical derivation for the solution. Substituting equation (16) back into the expression (10) for the MSE, then we get

$$\varepsilon_{\min} = E[d_k^2] - \mathbf{R}^{-1}P. \quad (17)$$

Therefore, the MSE can be rewritten as:

$$\varepsilon = \varepsilon_{\min} + (W - \hat{W})^T\mathbf{R}(W - \hat{W}). \quad (18)$$

It can be readily observed that the MSE performance function is a quadratic function of the weight vector with a bowl–shaped surface. Thus the adaptive weight updating process would seek the bottom of the bowl to achieve the optimal performance, and the weight vector corresponding to the minimum MSE is regarded as the optimal weight. To compute the optimal filter one must first compute $\mathbf{R}^{-1}$ and P. However, it would be difficult to compute $\mathbf{R}^{-1}$ and P accurately when the input data comprises a random stream of patterns (drawn from a stationary distribution). Thus, by direct calculating gradients of the square error (9) at the kth iteration [1–2, 13]:

$$\tilde{\nabla}\varepsilon_k = (\frac{\partial\varepsilon_k}{\partial b_0^k}, \frac{\partial\varepsilon_k}{\partial a_1^k}, \frac{\partial\varepsilon_k}{\partial b_1^k}, ..., \frac{\partial\varepsilon_k}{\partial a_N^k}, \frac{\partial\varepsilon_k}{\partial b_N^k})^{\mathrm{T}} = e_k(\frac{\partial e_k}{\partial b_0^k}, \frac{\partial e_k}{\partial a_1^k}, \frac{\partial e_k}{\partial b_1^k}, ..., \frac{\partial e_k}{\partial a_N^k}, \frac{\partial e_k}{\partial b_N^k}) = -e_k X_k, \quad (19)$$

where $e_k = (d_k - s_k)$, and $s_k = X_k^{\mathrm{T}}W_k$. Therefore, the recursive weights updating equation can be expressed as:

$$W_{k+1} = W_k + \mu(-\tilde{\nabla}\varepsilon_k) = W_k + \mu e_k X_k = W_k + \mu(d_k - s_k)X_k, \quad (20)$$

where the learning rate μ is used to adjust the convergence speed and stability of the weights updating process. Taking the expectation of (19), we get:

$$E[\tilde{\nabla}\varepsilon_k] = -E[e_k X_k] = \\ = -E[d_k X_k - X_k X_k^T W_k] = \mathbf{R}W_k - P = \nabla\varepsilon. \quad (21)$$

From equation (21), it can be found that the long–term average of $\tilde{\nabla}\varepsilon_k$ approaches $\nabla\varepsilon$ hence $\tilde{\nabla}\varepsilon_k$ can be used as unbiased estimate of $\nabla\varepsilon$. If the input data set is finite (deterministic), then the gradient $\nabla\varepsilon$ can be computed accurately by collecting the different gradients $\tilde{\nabla}\varepsilon_k$ over all training patterns X_k for the same set of weights. The steepest descent search is guaranteed to search the Weiner solution provided the learning rate condition (22) is satisfied [1–2]:

$$0 < \mu < \frac{2}{\lambda_{\max}}, \quad (22)$$

where $\lambda_{\max}$ represents the largest eigenvalue of $\mathbf{R}$. As for learning rate μ, increasing it results in faster convergence rate at the trade–off of losing accuracy and increasing overshoots in transient response.

The following sections would focus on the theoretical derivation to achieve the optimal solution of the error performance function. Here the input data vector X_k is supposed to be statistically independent of the previous data vectors X_j ($j<k$) [10–14]. Furthermore, the noise samples $\{n_k\}$ are assumed to constitute a white noise process with a symmetric, zero mean probability density function. And each weight vector W_k is statistically independent of the input vector X_k and the noise samples. Moreover, the step–size parameter is small enough such that the excess mean–square error at the kth iteration is much smaller than the minimum MSE near convergence.

The mean–square–error (MSE) and misadjustment

Followed by the above assuming, the estimation error of ADALINE can be rewritten as [1–2, 10–13]:

$$\varepsilon_k = (\hat{W}^T X_k + n_k) - W_k^T X_k = n_k - M_k^T X_k, \quad (23)$$

where the vector M_k is defined as the difference between the weight vector at kth iteration and the optimal weight vector:

$$M_k = W_k - \hat{W}. \quad (24)$$

Therefore, the iteration equation for the weight error vector can be derived as:

$$M_{k+1} = M_k + \mu f(\varepsilon_k) X_k = \\ = M_k + \mu f(n_k - M_k^T X_k) X_k. \quad (25)$$

The error function can be rewritten by using the Taylor series expansion [1–2] about the noise samples n_k, hence:

$$f(\varepsilon_k) = f(n_k - M_k^T X_k) = \sum_{i=0}^{\infty} \frac{f^{(i)}(n_k)}{i!} (-M_k^T X_k)^{(i)}. \quad (26)$$

where $f^{(i)}(x)$ denotes the ith derivative of the function $f(x)$. It should be noted that the Taylor series expansion is a linear approximation of nonlinear weight vector updating algorithm. For the sake of simplicity, only the lower order terms up to the second order derivative of the Taylor series are adopted for approximation. This approximation is reasonable when the excess mean–square error (EMSE) variance is less than 10% of the minimum mean–square error (MSE) variance [1–2].

Therefore, the weight error vector can be rewritten as:

$$M_{k+1} = M_k + \mu\{[f(n_k) - f'(n_k) M_k^T X_k] X_k + \\ + \frac{1}{2} f''(n_k)(M_k^T X_k)^2 X_k\}. \quad (27)$$

Taking the expectation of both sides, we get:

$$E[M_{k+1}] = E[M_k] + \mu\{E[f(n_k)]E[X_k] - \\ - E[f'(n_k)]E[X_k^T X_k]E[M_k] + \\ + \frac{1}{2} E[f''(n_k)]E[(M_k^T X_k)^2 X_k]\}. \quad (28)$$

It should be noted that the error function $f(x)$ is an odd function of x, hence:

$$E[f(n_k)] = E[f''(n_k)] = 0. \quad (29)$$

Therefore, the expectation (28) can be simplified as:

$$E[M_{k+1}] = \{I - \mu E[f'(n_k)]R\}E[M_k] = \\ = \{I - \mu_{eff} R\}E[M_k], \quad (30)$$

where $\mu_{eff}=\mu E[f'(n_k)]$, represents the effective adaptive step–size, or the learning rate in [8–16]. It can be observed that equation (30) matches the corresponding form for the LMS algorithm [1–2]. The effective adaptive step–size must be small enough thus the convergence is sufficiently close to the optimal weight vector to ensure the accuracy of the linear approximation using Taylor series expansion. The selection of the learning rate has been discussed in many previous publications [13–16, 24]. Normally, a compromise between the dynamic response and steady–state accuracy must be achieved, which are measured by two criteria, namely, the time constant (τ_i) and excess mean–square error (EMSE). The time constant with respect to the jth eigenvalue in the general error criterion adaptation is defined as [1–2]:

$$\tau_j = \frac{1}{\mu_{eff} \lambda_j}, \quad (31)$$

where λ_j represents the jth eigenvalue of the correlation matrix $\mathbf{R}$, which is the covariance matrix of the input vector X_k. The excess mean–square error of the adaptive weights updating algorithm, caused by the fluctuation in the weight coefficients, can be defined as:

$$E[(M_k^T X_k)^2] = E[(\sum_{j=1}^{N} m_{j,k} x_{j,k})^2] =$$
$$= \sum_{j=1}^{N} E[m_{j,k}^2 x_{j,k}^2] = \qquad (32)$$
$$= \frac{\mu E[f^2(n_k)] tr[R]}{2E[f^{'}(n_k)]}.$$

where tr[*] denotes the trace operation, and it should be noted that the weight vector M_k and the input vector X_k are assumed to be independent. The misadjustment is thus defined as:

$$\sigma = \frac{E[(M_k^T X_k)^2]}{E[n_k^2]} = \frac{\mu E[f^2(n_k)] tr[R]}{2E[f^{'}(n_k)] E[n_k^2]}. \qquad (33)$$

Since the error function $f(\varepsilon_k)=\varepsilon_k$ for the present case, the above equation reduces to:

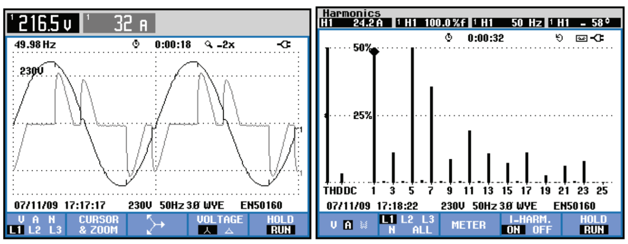
$$\sigma_{ADALINE} = \frac{\mu_{ADALINE}}{2} tr[R], \qquad (34)$$

which is a well–known result in previous literatures [1–2].

Experimental results and discussions

To verify the validity of the ANC–based ADALINE scheme, the experimental results of the thyristor rectifier load is utilized as the input data for training the adaptive estimation algorithm.

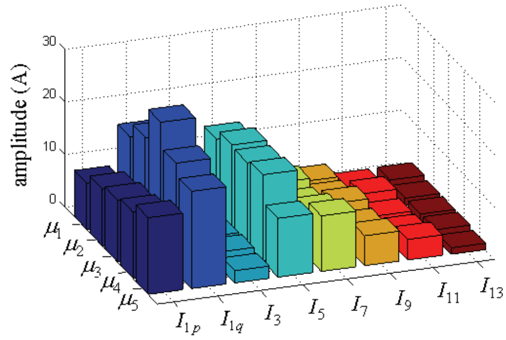
Fig. 2(a) shows the waveform of the grid voltage and the nonlinear load current and Fig. 2(b) shows the FFT spectrum of the load current, which are recorded using Fluke 435 power quality analyzer. The sampled nonlinear load current is processed by the digital signal processor (DSP) TMS320F2812 from Texas Instrument to test the performance of the ADALINE for individual harmonic estimation, which is programmed by using C++ and the assembly language on the code composer studio (CCS 3.3) platform.



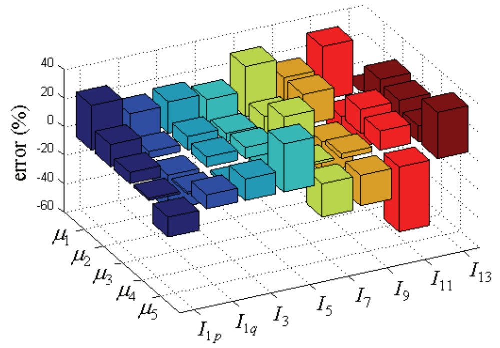
a) b)

Fig. 2. Experimental results of the nonlinear load currents with respect to the grid voltage and the FFT spectrum of the thyristor rectifier load current obtained from Fluke 435 power quality analyzer

Fig. 3 shows the experimental results of the individual harmonic components and the estimation error under different step–sizes, which varies from 0.005 to 0.025 with a step increase of 0.005, corresponding to μ_i (i=1 to 5). It should be noted from Fig. 3 that the symbols I_{1p} and I_{1q} represent the amplitude of fundamental active and reactive component, and the I_k (k=3 to 13) represents amplitude of the individual harmonic component, obtained from the calculated data from the CCS software. The estimated signal of Fig. 3(a) is compared with the measured data from Fluke 435 power quality analyzer to calculate the estimation error in order to check the performance of the ADALINE algorithm. It can be observed that excessive small or high step–size results in remarkable estimation error. The optimal performance of the ADALINE, i.e., the smallest estimation error, is achieved when the step–size is selected as μ=0.02.



a)



b)

Fig. 3. The experimental results of the ANC–based adaptive estimation algorithm under different step–size parameters from the fixed–point digital signal processor (DSP). (a). The obtained amplitudes of the fundamental active, reactive components and the harmonic components; (b).The estimation error (%) of the individual harmonic component

Conclusions

This paper systematically reviews the state–of–the–art techniques of the adaptive signal processing methods for power quality conditioning applications using active noise control (ANC) method. The mathematical derivation of a typical ANC scheme, the adaptive linear neural network (ADALINE), is presented, followed by the discussion on properties of the mean–square–error and the convergence of the algorithm. The step–size selection is also discussed to achieve optimal performance of the adaptive estimation algorithm. Finally, the experimental results are presented to validate the theoretical derivations.

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The active noise control (ANC) is considered to be the fundamental concept of the adaptive signal processing techniques, which has been increasingly utilized for electric signal decompositions and reconstructions. Followed by an extensive literature survey, this paper aims to provide a systematical theoretical derivation of the ANC problem for power quality conditioning applications. The mathematical formulation of the ANC–based harmonic estimation problem is presented, and the discussion on the mean–square–error (MSE) and misadjustment issues are also reported. The validity and effectiveness of the ANC scheme is verified by the experimental results. Ill. 3, bibl. 24 (in English; abstracts in English, Russian and Lithuanian).

Янг Хан, Лин Ху, Ганг Яо, Ли-Дан Зхоу, Мансоор, Чен Чен. Исследование схемы обработки сигналов на основе контроля активных шумов в системах качества мочности // Электроника и электротехника. – Каунас: Технология, 2009. – № 8(96). – С. 9–14.

Дан обширный анализ контроля активных шумов и показано его преимущество при обработке цифровых сигналов. Описываются теоретические предпосылки определения контроля в системах качества мощности. Математически доказано величина погрешности данного анализа, эффективность предложенной схемы проверена экспериментально. Ил. 3, библ. 24 (на английском языке; рефераты на английском, русском и литовском яз.).

Yang Han, Lin Xu, Gang Yao, Li–Dan Zhou, Mansoor, Chen Chen. Adaptyvaus signalo apdorojimo galios kokybės sistemose schemos tyrimas taikant aktyvių triukšmų kontrolę // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2009. – Nr. 6(96). – P. 9–14.

Apžvelgta aktyviųjų triukšmų kontrolė (ATK) yra laikoma pagrindine koncepcija, taikoma adaptyviems skaitmeniniams signalams apdoroti. Ji vis plačiau taikoma elektriniams signalams atskirti ir sujungti. Atlikus išsamią literatūros šaltinių apžvalgą apibrėžtas ir nustatytas pagrindinis šio straipsnio tikslas – susisteminti teorines žinias apie aktyviųjų triukšmų kontrolę galios kokybės sistemose. Straipsnyje pateiktas ATK matematinis pagrindimas, matematiniai kvadratinės paklaidos teiginiai. ATK schemos efektyvumas patikrintas eksperimentiniais tyrimais. Il. 3, bibl. 24 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).