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A METHOD BASED ON ADAPTIVE LINEAR NEURAL NETWORK FOR HARMONIC ESTIMATION

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Abstract- In electrical systems, harmonics are electrical current or voltage signals containing frequencies equal to multiples of the fundamental frequency, which is 50 Hertz in Vietnam. Harmonics cause many negative effects on the elements of the distribution network. To accurately estimate amplitude values and phase angles of harmonic components, this paper researches the application of the adaptive linear (Adaline) neural network with a new weight updating rule for harmonic estimation. The weights and bias coefficients of the Adaline neural network are automatically adjusted and updated themselves whenever there is some fluctuation inside the input signal, this makes the estimated error reach the minimum value of 0. In addition, the Adaline weights adjusted according to the new updating rule are also used to determine the magnitudes and angles of harmonic components inside the signal. The harmonic estimation results are compared to the traditional fast Fourier transform (FFT) method. The advantage of Adaline is that the estimation results contain both frequency and time information about the input signal.

Keywords: Harmonic Estimation, Voltage Signal, Neural Network, Nonlinear Loads, Spectrum Analysis, Power Quality.

1. INTRODUCTION

Harmonics are simply understood as a type of interference wave that appears undesirable. They have a negative impact on the power quality of the distribution network [1]. In particular, when the harmonic current level is higher than the specified level, it is necessary to pay attention and monitor carefully. Harmonics in electrical systems can result in increasing the temperature of the elements as well as causing interference with the distribution network. Therefore, harmonics are considered to be a bad wave for electrical equipment, which has serious effects on the electrical system as well as machinery and equipment [2]. In an industrial sector, the current harmonic is caused by most power electronic devices. Modern industrial factories consist of many equipment components that may make to the total harmonic distortion, a several instances including variable frequency drives and induction motors driven by converters [3]. These units draw the alternating current to convert that into direct current and then produce an alternating current with variable frequency so that the induction motors can be precisely controlled. When the current is fed into the converter, it is not formed as a ideal waveform [4].

Harmonic waveforms are formed by nonlinear loads associated with electrical distribution systems. In it, the electric energy converters transform into many different forms, causing harmonic interference [5]. At the same time, nonlinear loads such as motor starting, electric drive systems, electronic equipment, electronic lights, computers, welding sources, etc. Currently, inverters are commonly used in many modern industries to control motors, ships, drilling rigs, pumps, etc. The accurate identification of harmonic components is very important to come up with solutions to eliminate harmonics in the power system [6, 7].

The aim of this work is to research the application of the Adaline network for estimating accurately harmonic components. For power quality detection, some Adaline-based methods have been compared for their advantages and disadvantages [8]. The adaptive linear element (Adaline) with a cascaded two-stage structure was presented in [9] for measuring both harmonics and interharmonics. The method had better accuracy and was also adopted for harmonic and interharmonic compensation units in real time. The active power filter proposed in [10] was fully designed using the Adaline neural networks to determine and mitigate harmonic from an AC power supply.

In this proposed filter, different learning approaches were also used to control the converter to create the reference signals. In the work [8], a successful algorithm based on the radial-basis-function neural network was given to identify the harmonic magnitudes of the measurement current. The unique two-fold Adaline for measuring the harmonic components of the measurement current was proposed in [11]. The method adopts the least mean square (LMS) method by using a constant and huge step-size for adjusting the vector of weights. Clonal Selection algorithm was applied in [12] for harmonic estimation. The approach applies an antibody population to find within a multi-dimensional space.

The technique based on the extended Kalman filter (EKF) to calculate and detect the voltage sag parameters was proposed in [13]. In the algorithm, a status-space of a voltage sag signal was given to formulate the voltage sag signal by a status-space modelling of EKF. The combination between the recursive least square, Adaline and Kalman filter was proposed for estimating harmonic components of a harmonic current signal [14]. In this method, Kalman filter and recursive least square techniques calculate the weight updating of the Adaline. The Adaline and feed-forward MNN-based control algorithms were proposed in [15] to estimate harmonics for shunt active power filter. The practical application for estimating the total harmonic distortion in distribution networks was proposed in [16]. In the work, the load flow technique based on the probabilistic harmonic was applied to the sample network.

The technique base on an improved FFT was accurately proposed in [9, 17] to estimate harmonics and interharmonics. In the method, a frequency domain interpolation method was carried out to calculate the fundamental frequency. Besides, the polynomial-based interpolatory approach was used to rebuild the sampled signal in time domain; it was done by applying the FFT for estimating the harmonic orders. Then, the frequency domain interpolation was used to seek the interharmonic orders. The RBF neural network for identifying the harmonic load was proposed in [18]. In the method, a microcontroller processes the harmonic load flow by the FFT technique as an analysis of the load current signals.

From the above overview, this paper proposes a method based on an Adaline neural network for estimating harmonic components. The key contributions of this work can be highlighted as follows: (*i*) The new weight updating rule for the Adaline network is proposed to accurately determine the amplitudes and angle phases of the harmonic components in power systems; (*ii*) The proposed detail algorithm with 7 steps can be performed for both simulation and measurement signals; (*iii*) The performance comparison between the proposed method and the FFT method is given to confirm the proposed method effectiveness.

2. THEORETICAL ANALYSIS

2.1. Adaline Background

The Adaline was applied to determine the time-varying amplitudes and phase angles of the fundamental and harmonic components from a signal as shown in Figure 1. The theoretical basis of Adaline is briefly overviewed [5, 19]. Consider a signal $Y(t)$ with Fourier series extension as [4] :

$$\begin{aligned} Y(t) &= \sum_{h=0,1,2,3,\cdots}^{H} A_h \sin\left(h\omega t + \varphi_h\right) + \varepsilon(t) = \\ &= \sum_{h=0,1,2,3,\cdots}^{H} \left(a_h \sin 2\pi hft + b_h \cos 2\pi hft\right) + \varepsilon(t) \end{aligned} \tag{1}$$

where, A_h is the magnitude and angle of the h-th harmonic order, φ_h is the phase angle of the h-th harmonic order, and $\varepsilon(t)$ is added to show the high orders and the random noise.

To establish the harmonic estimation formulation by applying the Adaline, the vectors X_k and W_k are used to represent for the pattern and the weight vectors as [8]:

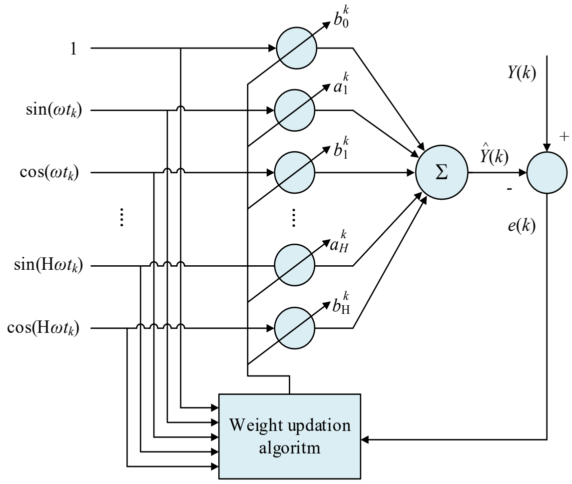


Figure 1. The modeling of the adaptive linear neural network

$$X_k = \left[1,\ \sin\omega t_k,\ \cos\omega t_k,\ \ldots,\ \sin H\omega t_k,\ \cos H\omega t_k\right]^T \tag{2}$$

$$W_k = \left[b_0^k,\ a_1^k,\ b_1^k,\ a_2^k,\ b_2^k,\ \ldots,\ a_H^k,\ b_H^k\right]^T \tag{3}$$

2.2. Weight Updating Rules

The square error for the pattern X_k is formulated as [11]:

$$\begin{aligned} \varepsilon_k &= \frac{1}{2}\left(d_k - X_k^T W_k\right)^2 = \frac{1}{2} e_k^2 = \\ &= \frac{1}{2}\left(d_k^2 - 2 d_k X_k^T W_k + W_k^T X_k X_k^T W_k\right) \end{aligned} \tag{4}$$

where, d_k is the output of desired scalar. ε is the error of mean square (MSE) which is established by expectating two sides of Equation (4):

$$\varepsilon = E\left[\varepsilon_k\right] = \frac{1}{2}E\left[d_k^2\right] - E\left[d_k X_k^T\right]W_k + \frac{1}{2}W_k^T E\left[X_k X_k^T\right]W_k \tag{5}$$

where, the vector weights are supposed as a constant at each W_k while calculating the expectation. The objective is to search the optimisation of the vector $\widehat{W}_k$ which can minimize the MSE of Equation (4). Equation (5) can be rewritten as [8]:

$$\varepsilon = E\left[\varepsilon_k\right] = \frac{1}{2}E\left[d_k^2\right] - P^T W_k + \frac{1}{2}W_k^T R W_k \tag{6}$$

where, R and P_T are determined as follows [8]:

$$P^T = E\left[d_k X_k^T\right] = E\left[\begin{pmatrix} d_k,\ d_k \sin\omega t_k,\ d_k \cos\omega t_k, \\ \ldots,\ d_k \sin H\omega t_k,\ d_k \cos H\omega t_k \end{pmatrix}\right] \tag{7}$$

$$\begin{aligned} R &= E\left[X_k X_k^T\right] = \\ &= E\begin{bmatrix} 1 & \sin\omega t_k & \ldots & \cos H\omega t_k \\ \sin\omega t_k & \sin\omega t_k \sin\omega t_k & \ldots & \sin\omega t_k \cos H\omega t_k \\ \ldots & \ldots & \ldots & \ldots \\ \cos H\omega t_k & \cos H\omega t_k \sin\omega t_k & \ldots & \cos H\omega t_k \cos H\omega t_k \end{bmatrix} \end{aligned} \tag{8}$$

where, R is a matrix with all symmetric and real elements, and ε is a quadratic function of the weight vector.

Besides, the gradient $\nabla\varepsilon$ according to the MSE of Equation (4) can be established according to [14]:

$$\nabla\varepsilon=\left(\frac{\partial\varepsilon}{\partial b_0^k},\frac{\partial\varepsilon}{\partial a_1^k},\frac{\partial\varepsilon}{\partial b_1^k},\ldots,\frac{\partial\varepsilon}{\partial a_H^k},\frac{\partial\varepsilon}{\partial b_H^k}\right)^T= \\ =-P+RW_k \quad (9)$$

As presented in Equation (9), the gradient $\nabla\varepsilon$ is a linear function of the weight vector. The best weight solution, $\hat{W}_k$, is determined by establishing $\nabla\varepsilon = 0$:

$$-P+R\hat{W}_k=0 \quad (10)$$

The final solution of the Equation (10) is named by the Weiner approach:

$$\hat{W}_k=R^{-1}P \quad (11)$$

The Weiner approach match to the point in the weight space which is the minimum value of the mean square error $\varepsilon_{\min}$. To determine the optimum filter, we must firstly calculate P and R^{-1}. However, it is difficult to calculate P and R^{-1} correctly when the input data consists of a random pattern. Therefore, the gradient $\nabla\varepsilon_k\%$ are calculated as follows [14]:

$$\nabla\varepsilon_k\%=\left(\frac{\partial\varepsilon_k}{\partial b_0^k},\frac{\partial\varepsilon_k}{\partial a_1^k},\frac{\partial\varepsilon_k}{\partial b_1^k},\ldots,\frac{\partial\varepsilon_k}{\partial a_H^k},\frac{\partial\varepsilon_k}{\partial b_H^k}\right)^T= \\ =e_k\left(\frac{\partial e_k}{\partial b_0^k},\frac{\partial e_k}{\partial a_1^k},\frac{\partial e_k}{\partial b_1^k},\ldots,\frac{\partial e_k}{\partial a_H^k},\frac{\partial e_k}{\partial b_H^k}\right)= \\ =-e_kX_k \quad (12)$$

where, $s_k = X_k^T W_k$ and $e_k = (d_k - s_k)$. The equation to update the weights is as follows [14]:

$$W_{k+1}=W_k+\mu\left(-\nabla\varepsilon_k\%\right)= \\ =W_k+\mu e_kX_k= \\ =W_k+\mu\left(d_k-s_k\right)X_k \quad (13)$$

where the rate of learning μ is added to control the speed of convergence and the process stability of updating weights. By taking the expectation of Equation (12), the Equation (14) is established:

$$E\left[\tilde{\nabla}\varepsilon_k\right]=-E\left[e_kX_k\right]= \\ =-E\left[d_kX_k-X_kX_k^TW_k\right]= \\ =RW_k-P=\nabla\varepsilon \quad (14)$$

From Equation (14), the long-term average of $\tilde{\nabla}\varepsilon_k$ approaches $\nabla\varepsilon$; therefore, $\tilde{\nabla}\varepsilon_k$ can be seen as an unbiased estimate of $\nabla\varepsilon$. The learning rate in Equation (15) is as follows:

$$0<\mu<\frac{2}{\lambda_{\max}} \quad (15)$$

where, the parameter $\lambda_{\max}$ in Equation (15) is the largest eigenvalue of the matrix R. When the MSE (ε) is minimized, the solution of the weight vector $\hat{W}$ after the convergence is determined as follows:

$$\hat{W}=\left[b_0,\ a_1,\ b_1,\ a_2,\ b_2,\ldots,\ a_H,\ b_H\right]^T \quad (16)$$

The error $e(k)$ is used to train the algorithm to update the weights of the Adaline. To establish a strong prediction of the signal, the technique minimizes the average square error between the actual and estimated signals. The Widrow-Hoff learning rule is given in [11]. To make the algorithm faster and to reduce the convergence problems, a modified weight adaptation law [5] is used, according to:

$$W(k+1)=\begin{cases}W(k)+\dfrac{\mu e(k)y(k)}{x^T(k)y(k)} & \text{if } y(k)x^T(k)\neq 0\\ W(k) & \text{if } y(k)x^T(k)=0\end{cases} \quad (17)$$

with $y(k)=0.5\,\mathrm{sgn}(x(k))+0.5x(k)$ (18)

where, $W(k)$ is neuronal weight, $x(k)$ the vector of input and $e(k)$ the error at instant k.

2.3. Proposed Flowchart Algorithm

After calculating the weights by the Widrow-Hoff learning rule according to Equations (17) and (18), the magnitude A_h and angle φ_h of the h-th harmonic in Equation (1) is given by [20]:

$$A_h=\sqrt{W(2h-1)^2+W(2h)^2}=\sqrt{a_h{}^2+b_h{}^2} \quad (19)$$

$$\varphi_h=\tan^{-1}\left(\frac{W(2h)}{W(2h-1)}\right)=\tan^{-1}\left(\frac{b_h}{a_h}\right) \quad (20)$$

where, $-\pi \le \varphi_h \le \pi$. This paper proposes the Adaline-based harmonic estimation method with the flowchart as shown in Figure 2.

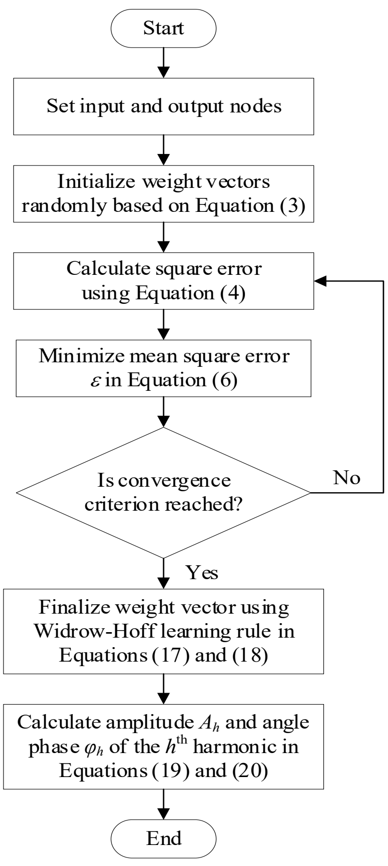


Figure 2. The flowchart of Adaline-based harmonic estimation method

The proposed method includes 7 steps as follows:
Step 1: Set the input and outputs nodes of the Adaline (Figure 1)
Step 2: Initialize the weight vectors randomly based on Equation (3)
Step 3: Calculate the square error using Equation (4)
Step 4: Minimize the mean square error ε in Equation (6)
Step 5: Check the convergence criterion of Step 4. If the convergence criterion is not reached, return to Step 3; otherwise go straight to Step 6
Step 6: Finalize the weight vector applying Widrow-Hoff learning rule in Equations (17) and (18)
Step 7: Calculate the amplitude A_h and the angle phase φ_h of the h-th harmonic in Equations (19) and (20).

3. RESULTS AND DISCUSSION

In this section, the harmonic signals are generated by the mathematical formula and simulation process to evaluate the performance of the Adaline-based harmonic estimation method of this paper. First of all, the voltage signals are described by a mathematical formula whose parameters can be changed to easily generate many different scenarios. This means the amplitudes and angle phases of harmonics in the voltage signals are established, and the proposed method is then applied to estimate them. In addition, the R2021a Matlab/Simulink software is used to model and simulate a distribution network with nonlinear loads and renewable resources. Due to the nonlinear loads and renewable resources, current harmonics are produced in the network and it also results in voltage harmonics. Therefore, the current harmonics of this case study are used to verify the proposed method. Furthermore, the proposed method is compared with the fast Fourier transform [9] (as a traditional method) to verify its effectiveness for harmonic estimation. The voltage signal is modeled by a mathematical formula as follows:

$$v(t) = \sum_{h=1,3,5,...}^{H} \frac{1}{h}\sin(h\omega t) \qquad (21)$$

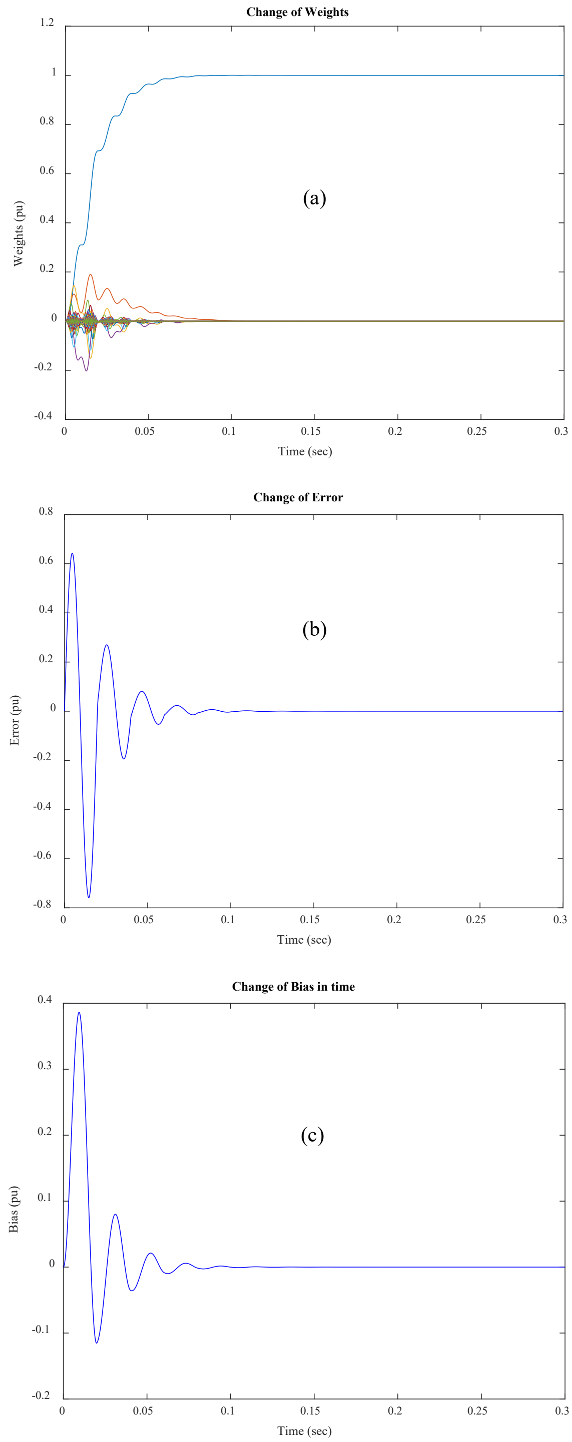
where, h is the harmonic order, H is the maximum harmonic order, ω is the angle velocity, and t is the time.

In this paper, the fundamental frequency and the sampling frequency are 50 Hz and 10 kHz, respectively. In addition, the maximum harmonic order is 11. The total simulation duration is established at 0.3 sec.

• Case 1: Sine voltage without harmonic

In this first case, the voltage signal in Equation (21) is assumed to exist only in the fundamental frequency component, which means that no harmonic component is present inside the voltage signal. Therefore, it is considered as the ideal voltage waveform. After generating the ideal voltage wave of the first case study, the paper applies the proposed method to estimate the harmonic components of the ideal voltage signal. The results of the proposed method are shown in Figure 3.

It is clear that the first 0.1 sec interval is the period of time during which the Adaline neural network adapts itself and updates the weights (Figure 3a) and bias coefficients (Figure 3c) to make the estimation error as in Figure 3b gradually stabilize to zero. When the Adaline neural network has been established in a stable state, the magnitude A_h and angle φ_h will be determined according to Equations (19) and (20). Harmonic spectral results of the ideal voltage signal of this case study performed by the proposed method and the FFT method are expressed simultaneously in Figure 3d. This result shows that the proposed method has given accurate harmonic estimation results and it can also contain information about the time of the initial signal.



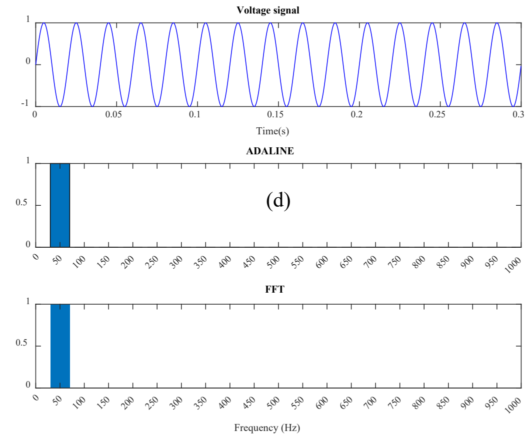


Figure 3. The harmonic estimation results of Case 1: (a) Change of weights, (b) Change of error, (c) Change of bias, (d) Harmonic estimation by Adaline and FFT

• Case 2: Voltage sag without harmonic

The second case study in this paper is to set the voltage sag without harmonics by assuming that by the time t = 0.15 sec the voltage amplitude will decrease from 1.0 pu to 0.5 pu. Thus, for the initial time interval from 0 to 0.15 sec, the harmonic estimation results of the Adaline are completely similar to the case 1. This can be clearly seen by the simulation results as shown in Figure 4. It is assumed that the phenomenon of voltage sag occurs at the time t = 0.15 sec, so the Adaline neural network must also adjust and update the weights (Figure 4a) and the bias coefficient (Figure 4c) to make the error gradually return to 0 as shown in Figure 4b.

• Case 3: Voltage with harmonic

In the third case study, the harmonic voltage signal is generated from the mathematical Equation (21). In the equation, the fundamental frequency component has an amplitude of 1.0 pu, the third order harmonic has an amplitude of 1/3 pu, the fifth one has an amplitude of 1/5 pu, the seventh one has an amplitude of 1/7 pu, the ninth one has an amplitude of 1/9 pu, and the eleventh one has an amplitude of 1/11 pu. Therefore, the harmonic voltage waveform of this case is shown in Figure 5d. When applying the Adaline method to estimate the parameter of this voltage signal wave, the weights (Figure 5a) and its bias coefficient (Figure 5c) will be adjusted to adapt and update themselves after each time step to make the estimation error between the estimated signal and the actual signal gradually reach 0 pu as shown in Figure 5b. In this case, the weights of the Adaline neural network have been adjusted much differently than in the previous two cases, and it is also from these weights that the amplitude values and angles of the harmonic components are determined. Figure 5d represents the harmonic spectral results of the voltage signal in this case of the proposed method and the FFT method. The voltage harmonic spectrum of these two methods is exactly the same, but the proposed method contains the time information of the original signal, whereas the FFT method contains only the frequency information of the original signal.

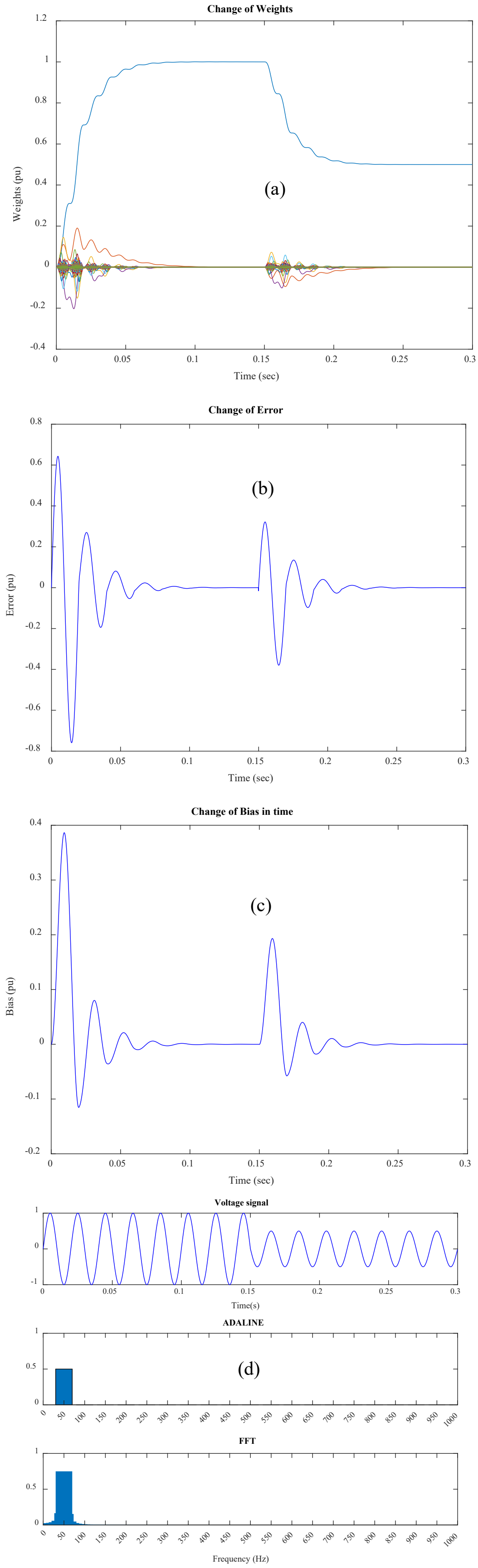
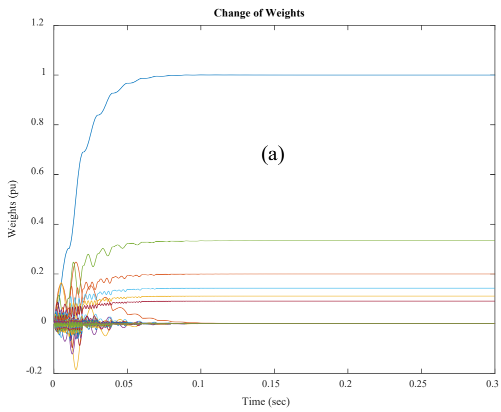
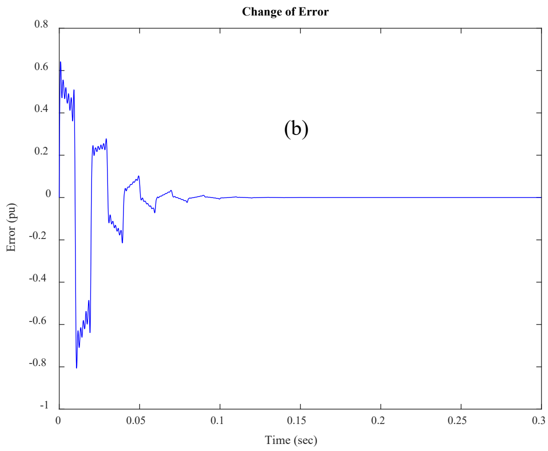


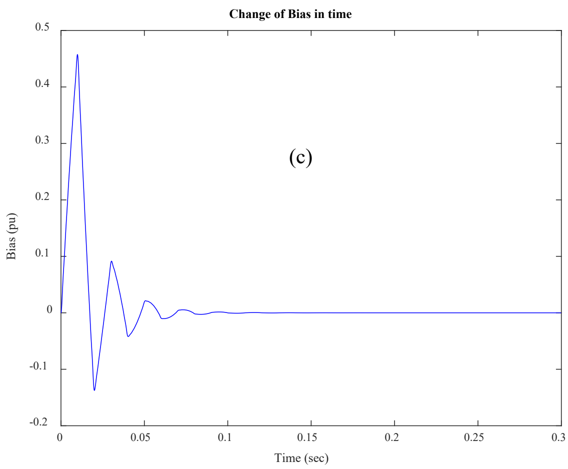
Figure 4. The harmonic estimation results of Case 2: (a) Change of weights, (b) Change of error, (c) Change of bias, and (d) Harmonic estimation by Adaline and FFT

• Case 4: Voltage sag with harmonic

The voltage signal in the fourth case is the voltage sag with harmonic which is generated from the voltage signal of the third case but the voltage sag will start from the time t = 0.15 sec with the amplitude reduced from 1.0 pu to 0.5 pu. Thus, the Adaline neural network applied to the voltage signal of this case has the results as shown in Figure 6. The weights and bias coefficients of the Adaline automatically adjust and update to make the estimation error equal to zero as shown in Figure 6b. The simulation results of voltage harmonic spectrum analysis by the proposed method and the FFT method are also compared as shown in Figure 6d.







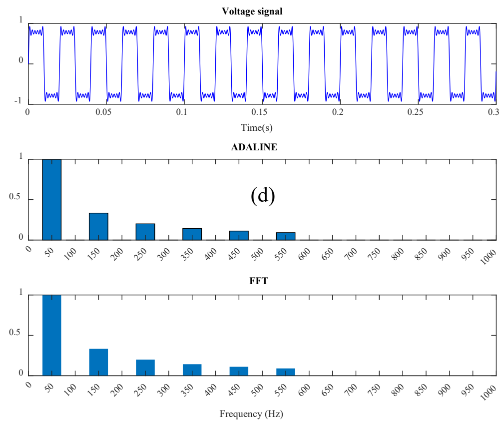
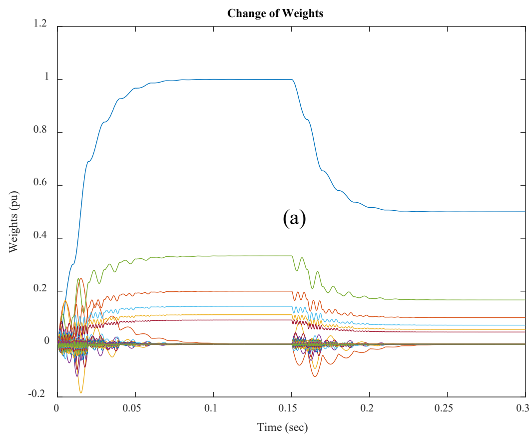
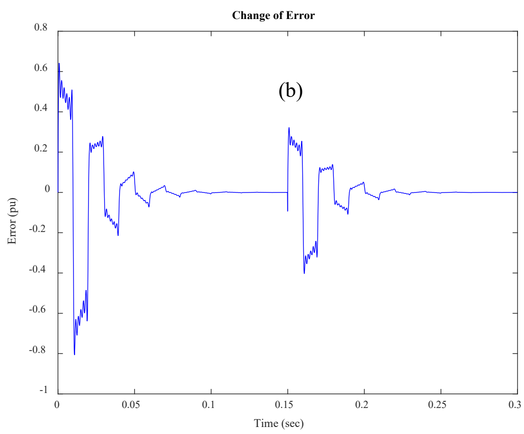
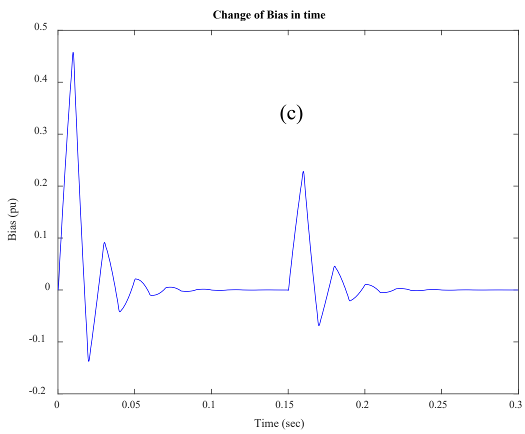


Figure 5. The harmonic estimation results of Case 1: (a) Change of weights, (b) Change of error, (c) Change of bias, and (d) Harmonic estimation by Adaline and FFT







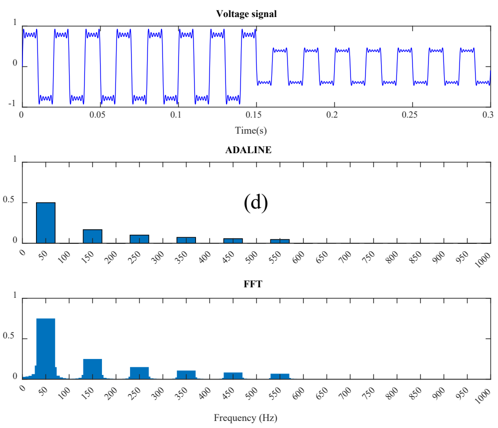


Figure 6. The harmonic estimation results of Case 4: (a) Change of weights, (b) Change of error, (c) Change of bias, and (d) Harmonic estimation by Adaline and FFT

4. CONCLUSION

The Adaline-based harmonic estimation method uses the new weighting update rule proposed in this paper. The amplitudes and angles of the harmonics are determined according to the Adaline weights, so the estimation results of the Adaline-based method contain both the time and frequency information of the original signal. This is considered an advantage over the traditional FFT method. The proposed method is applied to different voltage waveforms to evaluate the ability to estimate the magnitude and angle of the harmonic components. The voltage signals based on the mathematical formula are established by changing their input parameters to verify the proposed method. The weights and bias coefficients of the Adaline automatically adjust and update to minimize the estimation error between the input signal and the estimated signal. The estimation results of the proposed method will be applied to harmonic filters to improve the power quality in the distribution network.

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REFERENCES

[1] A.K. Srivastava, A. Tiwari, S.N. Singh, "Harmonic/Inter-Harmonic Estimation: Key Issues and Challenges", The 6th International Conference on Computing, Communication and Automation (ICCCA), IEEE, pp. 842-853, Arad, Romania, 2021.

[2] A. Taghvaie, T. Warnakulasuriya, D. Kumar, F. Zare, R. Sharma, M. Vilathgamuwa, "A Comprehensive Review of Harmonic Issues and Estimation Techniques in Power System Networks Based on Traditional and Artificial Intelligence/Machine Learning", IEEE Access, Vol. 11, pp. 31417-31442, 2023.

[3] B. Farhang Boroujeny, "Adaptive Filters: Theory and Applications", John Wiley and Sons, Chapter 3, pp. 48-79, 2013.

[4] R. Gregory, C. Azevedo, I. Santos, "Study of Harmonic Distortion Propagation from a Wind Park", IEEE Latin America Transactions, Vol. 18, No. 06, pp. 1077-1084, 2020.

[5] D.O. Abdeslam, J. Merckle, R. Ngwanyi, Y.A. Chapuis, "Artificial Neural Networks for Harmonic Estimation in Low-Voltage Power Systems", The 4th International ICSC Symposium on Engineering of Intelligent Systems, pp. 999-1009, 2004.

[6] P. Sundaramoorthi, G.S. Venkatesh, V.P. Moorthy, "DSTATCOM Based Additive and Subtractive Topology Multilevel Inverter for Improving Power Quality", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 51, Vol. 14, No. 2, pp. 36-45, June 2022.

[7] Y. Yaghoobi, A. Alduraibi, F. Zare, "Current Harmonic Estimation Techniques Based on Voltage Measurements in Distribution Networks", The 2018 Australasian Universities Power Engineering Conference (AUPEC), IEEE, pp. 1-6, Auckland, New Zealand, 2018.

[8] G.W. Chang, C.I. Chen, Y.F. Teng, "Radial-Basis-Function-Based Neural Network for Harmonic Detection", IEEE Transactions on Industrial Electronics, Vol. 57, No. 6, pp. 2171-2179, 2009.

[9] G. Chang, C. Chen, Y. Liu, M. Wu, "Measuring Power System Harmonics and Inter-Harmonics by an Improved Fast Fourier Transform-Based Algorithm", IET Generation, Transmission, Vol. 2, No. 2, pp. 192-201, 2008.

[10] D.O. Abdeslam, P. Wira, J. Merckle, D. Flieller, Y. A. Chapuis, "A Unified Artificial Neural Network Architecture for Active Power Filters", IEEE Transactions on Industrial Electronics, Vol. 54, No. 1, pp. 61-76, 2007.

[11] P. Garanayak, R. Naayagi, G. Panda, "A High-Speed Master-Slave Adaline for Accurate Power System Harmonic and Inter-Harmonic Estimation", IEEE Access, Vol. 8, pp. 51918-51932, 2020.

[12] L. Holanda, R. Rabelo, M. Lemos, D. Barbosa, "Power System Harmonics Estimation Using Clonal Selection Algorithm", IEEE Latin America Transactions, Vol. 11, No. 1, pp. 525-530, 2013.

[13] N.M. Khoa, D.D. Tung, "An Extended Kalman Filter for Detecting Voltage Sag Events in Power Systems", Journal of Electrical Systems, Vol. 14, No. 2, pp. 192-204, 2018.

[14] B. Subudhi, P. Ray, "Estimation of Power System Harmonics Using Hybrid RLS-Adaline and KF-Adaline Algorithms", The TENCON 2009-2009 IEEE Region 10 Conference, IEEE, pp. 1-6, Singapore, 2009.

[15] M. Qasim, V. Khadkikar, "Application of Artificial Neural Networks for Shunt Active Power Filter Control", IEEE Transactions on Industrial Informatics, Vol. 10, No. 3, pp. 1765-1774, 2014.

[16] X. Xiao, Z. Li, Y. Wang, Y. Zhou, "A Practical Approach to Estimate Harmonic Distortions in Residential

Distribution System", IEEE Transactions on Power Delivery, Vol. 36, No. 3, pp. 1418-1427, 2021.
[17] J.Z. Yang, C.S. Yu, C.W. Liu, "A New Method for Power Signal Harmonic Analysis", IEEE Transactions on Power Delivery, Vol. 20, No. 2, pp. 1235-1239, 2005.
[18] A.F. Mubarok, T. Octavira, I. Sudiharto, E. Wahjono, D.O. Anggriawan, "Identification of Harmonic Loads Using fast Fourier Transform and Radial Basis Function Neural Network", The 2017 International Electronics Symposium on Engineering Technology and Applications (IES-ETA), IEEE, pp. 198-202, Surabaya, Indonesia, 2017.
[19] I.P. Sutawinaya, I.N.G.A. Astawa, N.K.D. Hariyanti, "Comparison of Adaline and Multiple Linear Regression Methods for Rainfall Forecasting", The 2nd International Joint Conference on Science and Technology (IJCST), pp. 1-7, Bali, Indonesia, 2018.
[20] D.T. Viet, N.H. Hieu, N.M. Khoa, "A Method for Monitoring Voltage Disturbances Based on Discrete Wavelet Transform and Adaptive Linear Neural Network", International Review of Electrical Engineering, Vol. 11, No. 3, pp. 314-322, 2016.

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