Learning and adaptive linear neural network for enhancing harmonics compensation

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Abstract—in his paper, the configuration characteristic of shunt active power filter (APF) was analyzed, as well as the adaptive linear neural network. In order to improve the dynamic performance of a control system and estimate harmonic distortion from nonlinear load current, a combination strategy based on the Fourier series analysis of the current signals and LMS training algorithm is presented. This control strategy was applied on industrial prototype simulation and field test, the experimental result shows that system compensation could effectively reduce the total harmonic distortion (THD) values. And it is most effective under different conditions of nonlinearity of industrial applications.

Keywords- Adaptive linear neuron (ADALINE); Reference current extraction; harmonics compensation;

I. INTRODUCTION

There has been a continuous proliferation of nonlinear type of loads in industry as well as by the consumers. Rectifiers, inverters, AC regulator, and other nonlinear loads introduce voltage and current harmonics in power systems. Currents and voltages are thus nonsinusoidal and it is necessary to compensate the generated harmonics [1;2]. Active power filter can be employed to compensate harmonics in power systems [3;5]. In this way, the power distribution system sees the nonlinear load and the active power filter as an ideal resistor. The current compensation characteristic of the shunt active power filter is shown in Fig.1.

In this paper an improved scheme is proposed using Adaptive Linear Neuron (ADALINE). The ADALINE neural network uses to separate the fundamental component from the distorted supply current. Based on the Fourier series, this new decomposition of current signals allows defining the neural network inputs for which a Least Mean Squares (LMS) algorithm carries out the weights training. The method utilizes adaptive neurons (ADALINE) to process the signals obtained from the line. This current ADALINE extracts the fundamental components of the distorted line current signal and the output of the ADALINE is compared with distorted supply current to construct the modulating signal. This modulating signal is used to generate the PWM pulses that fed to the distorted line current. Thus the power quality will be maintained [6-7].

II. OVERALL DESIGN SCHEME

Adalines are simple dynamical learning systems by means of a linear combination of time-dependent signals. Determining the value of its internal weights, it referred to as the training, is achieved which effective algorithms such as the LMS learning rule. This particular form of nonlinear regression is fast and accurate. The simplicity of its architecture offers to the Adaline some other advantages: the possibility of interpreting its weights and the possibility of hardware implementation. Fig.2 shows an Adaline which is composed of an input vector (X), a weigh vector (W) and an activation function f (W). There is a close analogy between artificial neurons and biological neurons. The weight vector W = [W1 W2…Wn]T corresponds to the set of synaptic strengths of a biological neuron. The input vector X = [X1 X2…Xn] T of the Adaline corresponds to the set of electrical or chemical signals received by the synapses of the dendrites of a biological neuron. The activation function y = f (W) is the mathematical modeling of the behavior of the core of a biological neuron. Different activation functions are possible in neural networks. The Adaline neuron uses linear
activation functions so the output \( y \) is simply the sum of the weighted inputs
\[
y = f(W^T X) = W_1 X_1 + W_2 X_2 + \ldots + W_n X_n.
\]

Fig. 2 Adaptive Linear Neural Network (ADALINE) principle

When a neuron is excited it produces an output \( y \) which depends on its inputs. In an Artificial Adaline Neuron these modifications correspond to weight changes. The \( W \) vector is constantly modified during the life of the neuron or during the training or learning process. In the theory of artificial neural networks the learning process may be divided in two major categories: on-line and off-line training. The Adaline is an on-line trained neuron; this means that the training process of the Adaline is carried all time. Other kinds of neural networks are trained only once so that the network is effectively used only after a fixed set of synaptic weights is obtained (generally after a very long training process). A learning rule must be found to correctly update (or modify) the weight vector \( W \) of an artificial neuron. Since neurons are generally part of a more complex system which is capable to learn or acquire knowledge (the human brain, for instance) the process of synaptic weight updating is called a learning process. One says that a neuron is undergoing a learning process when \( W \) is being updated.

Fig. 3 shows how this is done. A periodic waveform can be expanded by Fourier analysis of the time function. This can be achieved if the inputs of the Adaline are sine and cosine functions of fundamental and harmonic frequencies. The series contains \( N \) oscillatory components and one constant component. The trigonometric functions have angular frequencies \( n \omega \), where \( n \) is the harmonic order (\( n=1 \) corresponds to the fundamental frequency).

\[
y_d(t) = A_0 + \sum_{n=1}^{N} C_n \sin(n \omega t + \phi_n)
\]

(2)

\( \varepsilon \) is the error between the output of the neuron and the desired output \( \varepsilon = y - y_d \).

The learning rate \( \alpha \) is an important parameter. A high \( \alpha \) increases the learning speed but cannot warrant an accurate learning (i.e., the minimum error between the output and the desired output may be too high). A small \( \alpha \) decreases the learning speed but can provide a small error.

III. ADALINE BASED FOURIER SERIES

In the previous section it was seen that the weights of the Adaline are updated by the \( \Delta \)-rule so that the error \( \varepsilon \) is minimum. This means that the output \( y \) of the Adaline is forced to follow a desired output \( y_d \). If \( y \) is a time-varying signal the adapting or learning process must be carried in real time and must be fast enough in order to produce a small error at every time instant. As discussed previously, a reasonably high (but small enough to provide a small error) value of \( \alpha \) allows a fast convergence, thus the Adaline weight vector \( W \) can be adapted in real time so that \( y = y_d \) even if \( y_d \) changes with time and is not periodic. After a brief adapting process the weight vector \( W \) becomes quasi stationary (because \( \varepsilon \) becomes low and the weight increases or decreases become small) if \( y_d \) is periodic, i.e., the Adaline learns how to generate the output \( y \) (so that \( y \approx y_d \)). Whenever the waveform of \( y_d \) is altered another adapting process is started so that a new vector \( W \) is determined (with a low \( \varepsilon \) at the end of the process), i.e., the Adaline need to learn again. The adaptive behavior of the Adaline can be used to find the Fourier series approximation of the signal \( y_d \). This can be achieved if the inputs of the Adaline are sine and cosine functions of fundamental and harmonic frequencies.

In equation (1):

\[
W(k+1) = W(k) + \alpha \varepsilon \frac{X(k)}{X^T(k)X(k)}
\]

(1)

The index \( k \) corresponds to the discrete instant \( kT \), \( \alpha \) is the learning rate of the neuron.
Equation (2) may be rewritten as (3), where each oscillatory component is expressed as a sum of two trigonometric functions.

\[ y_d(t) = A_0 + \sum_{n=1}^{N} C_n \sin(nwt + \varphi_n) + \sum_{n=1}^{N} B_n \cos(nwt) \]

The relation between the amplitudes of the oscillatory terms of Equations (2) and (3) is given by equation (4) and the displacement angle \( \varphi_n \) is given by equation (5). Equation (5) is not used in the compensation method proposed in this paper because the Fourier series in the form of equation (3) is used. Equation (4) is used because the compensation method needs to determine the amplitudes of the fundamental electric currents, as will be explained later.

\[ C_n = \sqrt{A_n^2 + B_n^2} \]
\[ \varphi_n = \tan^{-1} \frac{B_n}{A_n} \]

Equation (6) is the discrete form of equation (3), because the compensation method is intended to be implemented in digital processors. It is convenient to write equation (6), where the index \( k \) corresponds to the \( k \)-th discrete time instant. The sampling interval \( T \) is the same used in the \( \Delta \)-rule of Equation (1). When the Adaline of Fig.3 is used to determine the Fourier series of \( y_d \) the weight vector \( W \) undergoes an adaptive updating process with the \( \Delta \)-rule of equation (1). If the error \( e \) is sufficiently small the components of the weight vector are the coefficients of the Fourier series of the time function \( y_d \).

\[ y_d(t) = A_0 + \sum_{n=1}^{N} A_n \sin(nwkt) \]
\[ + \sum_{n=1}^{N} B_n \cos(nwkt) \]

For simplicity, the input vector \( X \) (in the discrete form) and the weight vector \( W \) of the Adaline of Fig. (2) is written in equations (7) and (8).

\[ X = [1 \sin(wkt) \cos(wkt) \sin(2wkt) \cos(2wkt) \ldots \sin(Nwkt) \cos(Nwkt)]^T \]
\[ W = [A_0 A_1 A_2 A_3 \ldots A_N B_N] \]

IV. DETERMINATION OF REFERENCE COMPENSATING CURRENTS

The basic principle of the proposed control system to get the reference compensating currents of shunt APF is shown in Fig.4, where the figure shows the basic elements of control system. This scheme is mainly composed of an adaptive linear neural network (Adaline), phase locked loop circuit (PLL) and hysteresis current controller. The adaptive ANN extraction circuit, hysteresis control and the PLL circuit are integrated as an overall mode of adaptive shunt APF. In this circuit, the Adaline network will take information from the nonlinear load currents to estimate the reference compensation currents by identifying the harmonics with a Fourier expansion of the load currents and direct component of supply voltages. The PLL circuit generates sinusoidal signals with constant unit amplitude, even if the supply voltage has a distortion. Finally, the reference compensating currents of shunt APF are compared with its actual and the error fed to hysteresis current controller to obtain the switching of voltage source inverter (VSI) for injecting phase-opposite the harmonic currents in the power system. The following subsection outline he detailed control schemes of the proposed system.

The harmonic and reactive compensation of the proposed system using Adaline-based approach is outlined as follows: Considering phase (a) as studying case using Fourier series, the nonlinear load current waveform can be represented by equation (9):

\[ i_a(t) = \sum_{n=1}^{N} I_n \sin(nwkt + \varphi_n) \]
In harmonic extraction procedure, the equation (9) can be expanded as follows:

\[
i_n(t) = \sum_{n=1}^{N} I_n \sin(nwt) \cos(\phi_n) + I_n \cos(nwt) \sin(\phi_n)
\]

(10)

Where:

- The first term without summation corresponds to fundamental frequency;
- \(I_1\) and \(\phi_1\) are the magnitude and phase angle respectively.

Equation (11) can be written as:

\[
i_n(t) = W_1 \sin(wt) + W_2 \cos(wt) + W_{2n-1} \sin(nwt) + W_{2n} \cos(wt)
\]

(12)

Where:

- \(W_1 = I_1 \cos(\phi_1)\) and \(W_2 = I_1 \sin(\phi_1)\)

Equation (13) is the discrete form of equation (12)

\[
i_k(k) = W_1 \sin(wkT) + W_2 \cos(wkT) + W_{2n-1} \sin(nwkT) + W_{2n} \cos(nwkT)
\]

(13)

The proposed control method is based on three Adaline neurons (Adaline neuron for each phase), but for simplicity, the studying will be investigated in one phase. To construct the adaptive ANN (Adaline) for one phase, the equation (13) is used and according to equations (7) and (8) from the previous section, the input vector \(X\) to the adaptive ANN is first determined as:

\[
X = [\sin(wkT) \cos(wkT) \sin(2wkT) \cos(2wkT) ... \sin(nwkT) \cos(nwkT)]
\]

And the weight vector \(W\) of the Adaline is:

\[
W = [W_1 \ W_2 \ W_3 \ ... \ W_{2n-1} \ W_{2n}]
\]

Fig.5 describes the Adaline structure with the input vector(X) being the AC components and the weights (W) correspond to the amplitudes of each harmonic current multiplied with alternatively \(\cos \varphi\) or \(\sin \varphi\). As shown in Fig.5, the output of the neuron is sum of the product WTX, which itself is estimated current (iLa est) of nonlinear load. The error \(\varepsilon_a\) is the difference between the output of the neuron (iLa est) and the measured nonlinear load current (iLa). This error signal is then propagated backward through the network, against the direction of synaptic connection. The synaptic weights are adjusted so as to make the actual response of the network move close to the desired response. The learning process performed with the error back-propagation algorithm is called back-propagation learning. Back propagation was created by "Widrow" (the Least Mean Square LMS). The Least Mean Square (LMS) algorithm can be considered a special case of the \(\Delta\)-learning rule; it is independent of the activation function of neurons. Based on the LMS learning rule this model represents the simplest intelligent self-learning system that can adapt itself to achieve a given linear modeling task. The problem consists in finding a suitable set of weights such that the input-output behavior of the Adaline becomes close to a set of desired input-output data points linked with a linear relationship. The Adaline weights are solved using an iterative linear LMS algorithm in order to minimize the estimation error. The LMS algorithm is designed with a single linear neuron model see (Fig.5); in this case the design of the LMS algorithm is very simple. The Adaline weights are adjusted according to:

\[
W_{k+1} = W_k + \alpha \varepsilon_a X(k)
\]

(14)

Where \(\alpha\) is learning rate or called convergence coefficient chosen between 0 and 1. As shown by Fig.5. The amplitude of fundamental current \(I_{pa}\) for phase (a) is extracted from the Adaline's weights using the first and second elements of the vector \(W\) of the Adaline as follows:

\[
I_{pa} = \sqrt{W_1^2 + W_2^2}
\]

(15)

A similar situation takes place in other Adalines for phases a,b and hence three values of the amplitudes of fundamental currents \(I_{pa}, I_{pb}\) and \(I_{pc}\) can be obtained. These three values are averaged to balance the system written as:
To achieve the target of pure sinusoidal wave shape in source current with a nearly unity power factor, the dc capacitor regulator with PI control is used as a basic element of the proposed control as shown in Fig.5. In order to regulate the dc-link voltage of the voltage source inverter (VSI) and keep constant, the sensed dc-link voltage is subtracted by its reference value, and then the error signal is processed in the PI control. The output of the dc-link voltage controller is $\Delta i$, which is necessary to regulate the amplitude of the fundamental sinusoidal current. Then the averaged of amplitudes of fundamental currents ($I_{pav}$) is added to the output of the dc-link voltage controller ($\Delta i$) and the result is multiplied with the output of PLL circuit in order to generate the active component current (in-phase with supply voltage) for every phase as follows:

$$I_{pa} = (I_{pav} + \Delta i) \sin(\omega t)$$

$$I_{pb} = (I_{pav} + \Delta i) \sin(\omega t - 120^\circ)$$

$$I_{pc} = (I_{pav} + \Delta i) \sin(\omega t + 120^\circ)$$

Finally, the estimation load currents, which are output of Adaline neurons ($i_{Lest}$) are subtracted from the active component currents $I_p$ (in-phase with supply voltages), the reference currents of the shunt APF can be obtained the following equation.

V. EXPERIMENTAL TESTS

The three-phase shunt active power filter laboratory prototype has been implemented with the specified system parameters in Appendix. The proposed control algorithm is implemented using digital signal processor DSP (DS1104) manufactured by the TI-company and developed under the environment of MATLAB. It can be shown in Fig.6.
While Fig.8 shows the source current before and after compensation when the firing angle of controlled rectifier $\alpha = 40^\circ$.

Through experimental results, it is revealed that the supply currents after compensating were found to be sinusoidal and in phase with its respective supply voltage, which was consistent with the simulation shown above. For this test, the outcome indicates that the proposed method is useful for the active power filter studies and it indicates the effectiveness of the proposed controller for shunt APF under different conditions [12].

VI. CONCLUSIONS

A new strategy to estimate harmonic distortion from nonlinear load current has been proposed. An Adaline neural network has been presented to determine precisely the necessary currents in order to eliminate harmful harmonics. The proposed strategy was based on the Fourier series analysis of the current signals and LMS training algorithm carries out the weights. An experimental shunt APF has been carried out on DSP to explore the advantages and practical implementation with the proposed control strategy. The simulations and experimental results have proven good performances and verify the feasibility of the proposed algorithm, and it is most effective under different conditions of nonlinearity of industrial applications.

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