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Adaline-based estimation of power harmonics

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Abstract. A new strategy to estimate harmonic distortion from an AC line is presented. An ADALINE neural network is used to determine precisely the necessary currents in order to cancel harmful harmonics. The proposed strategy is based on an original decomposition of the measured currents to specify the neural network inputs. This new decomposition is based on the Fourier series analysis of the current signals and a modified LMS training algorithm carries out the weights. This new estimation strategy appreciably improves the performances of traditional compensating methods and is valid both for single-phase and three-phase systems. The proposed strategy also allows to extract the harmonics individually.

1 Introduction

The current development of neural networks always opens prospects for new applications in various fields. In this work, we show how an ADALINE network can identify harmonic currents in an active power filtering system.

The deterioration of currents and voltages in electrical networks is due to the presence of nonlinear loads (rectifiers, variable speed transmissions, lighting, etc), absorbing nonsinusoidal currents. These harmonic currents circulate in the electrical network, disturb the correct operation of the components and can even generate their destruction.

The harmonic compensators, called Active Power Filters (APF), are advanced solutions for eliminating harmonic distortion [1]. They adapt easily to variations of the electrical network load. Further, no changes are required on the installation neither of the energy supplier nor that of the consumer.

The performances in terms of harmonic compensation strongly depend on the selected identification method. Indeed, an efficient control device will not be able to make the sufficient corrections if the harmonic currents are badly identified. For this reason, several identification methods were developed in the past.

The identification method of the real and imaginary instantaneous powers is largely used in active filtering systems. In [2], we replaced low-passes filter by ADALINE networks. Significant improvements were obtained in simulations and also on real applications, but the method is only applicable for three-phase systems.

In this work, we present an original identification approach valid for three-phase and single-phase systems. It uses ADALINE neural networks to separate harmonics from the fundamental frequencies. Based on Fourier series, this new decomposition of the current signals allows to define the neural network inputs for which an LMS algorithm carries out the weights training. The facility of use, as well as the parallel unfolding of computations, makes this approach fast and effective.

In the following section, we present the principle of system harmonic control. In section 3, we describe the principle of the identification method based on the new decomposition of current signals. Finally, in section 4, we give the simulation results.

2 Harmonic compensation in electrical systems

The harmonic compensation is of high importance for the energy suppliers as well as consumers. The APF thus constitutes the solution the most commonly used today in industry [3]. These systems are placed in derivation between the nonlinear load and the electrical supply network. Only a small portion of the energy is processed, resulting in greater overall efficiency and increased power processing capability.

An identifying module estimates the harmonic currents from the AC line and a control module injects these currents in the network. The second module strongly depends on the first one. Indeed, if the harmonic currents are badly identified, this inevitably involves a lower quality of the compensation.

Several methods can be used to estimate the harmonic currents in an electrical network [1, 2]. The new method that we propose makes it possible to treat the three phases in an independent way. The principle is based on the simultaneous estimate of the amplitude of the active fundamental component and the reactive fundamental component of the current absorbed by the load [5]. The compensation of the harmonic and/or the fundamental reactive component is done by the generation of sinusoidal signals of unit amplitude. The method is appropriate for the single-phase and three-phase currents systems and does not require the use of a PLL (Phase-Locked Loop).

3 An new ADALINE harmonic estimator

The ADALINE is a simple dynamical learning system by means of a linear combination of time-dependent signals. Introduced by Widrow [6] with the LMS (Least Mean Square) learning rule, the ADALINE is now widely used in signal processing theory for signal estimation and prediction.

The advantage of the ADALINE is the possibility of interpreting the weights, which generally cannot be done with multi-layer neural networks. The simplicity of its architecture is an additional advantage for a possible hardware implementation.

The originality of this work is the decomposition of the current in frequency components which leads to a new definition on the inputs of the ADALINE and which is developed thereafter. For each phase, after the measurement on the electrical supply network, the current can be expanded by Fourier analysis as a sum of cosine and sine frequency components in the following way:

$$I_s(t) = \underbrace{I_{11}\cos(\omega t-\alpha)+I_{12}\sin(\omega t-\alpha)}_{I_{sf}(t)} + \underbrace{\sum_{n=2,\ldots,N}\left[I_{n1}\cos n(\omega t-\alpha)+I_{n2}\sin n(\omega t-\alpha)\right]}_{I_{sh}(t)}, \quad (1)$$

with ω the fundamental frequency, α the phase between current and load voltages, I_{11} and I_{12} the cosine and sine frequency components of fundamental current, and I_{n1} and I_{n2} the cosine and sine frequency components of the harmonics current.

$I_{sf}(t)$ represents the fundamental current and $I_{sh}(t)$ the harmonics current. This decomposition can be used directly as inputs of an ADALINE neural network as suggested by [4]. For the three-phase case, better performances were however obtained in [2] by a decomposition in a two-phase reference plant (the instantaneous active and reactive powers, IARP). The objective of the new method is thus to reach these same performances by considering each phases of the electrical supply network independently.

Let us consider current I_s of the equation (1) be absorbed by the nonlinear load on the first phase (for $\alpha = 0$). By multiplying this equation respectively by $\sin \omega t$ and $\cos \omega t$ we obtain:

$$I_s(t)\sin\omega t = \frac{1}{2}\begin{bmatrix} I_{12} - I_{12}\cos 2\omega t + I_{11}\sin 2\omega t + \\ \sum\limits_{n=2...N} \begin{matrix} I_{n2}\cos(n-1)\omega t - I_{n2}\cos(n+1)\omega t + \\ I_{n1}\sin(n+1)\omega t - I_{n1}\sin(n-1)\omega t \end{matrix} \end{bmatrix}, \quad (2)$$

$$I_s(t)\cos\omega t = \frac{1}{2}\begin{bmatrix} I_{11} - I_{12}\sin 2\omega t + I_{11}\cos 2\omega t + \\ \sum\limits_{n=2...N} \begin{matrix} I_{n2}\sin(n+1)\omega t - I_{n2}\sin(n-1)\omega t + \\ I_{n1}\cos(n-1)\omega t - I_{n1}\cos(n+1)\omega t \end{matrix} \end{bmatrix}. \quad (3)$$

In these relations, only terms representing the continuous components are proportional respectively to the amplitude of the fundamental active current I_{12} and to the amplitude of the fundamental reactive current I_{11}. The expression (2) can be written as follows:

$$I_s(t)\sin\omega t = W^T.x(t), \qquad (4)$$

where W^T is the ADALINE weight vector and $x(t)^T$ is the network input vector composed of the cosine and sine components of the $n-$order harmonics:

$$W^T = [I_{12} \quad -I_{12} \quad I_{11} \quad ... \quad I_{n2} \quad -I_{n2} \quad I_{n1} \quad -I_{n1} \quad ...], \qquad (5)$$

$$\begin{aligned} x(t)^T = 1/2[1 \quad \cos 2\omega t \quad \sin 2\omega t \quad ... \\ ... \quad \cos(n-1)\omega t \quad \cos(n+1)\omega t \quad \sin(n+1)\omega t \quad \sin(n-1)\omega t \quad ...] \end{aligned} \qquad (6)$$

These sinusoidal signals are generated to compose, with a constant term, the input vector of the ADALINE. It is a way to introduce *a priori* knowledge in the neural network structure. The linear combination of the sinusoidal signals with the network weights in equation (4) results in an estimated signal composed of different harmonics. Figure 1 shows this topology. $I_s(t)\sin\omega t$ is the signal to be identified, $I_s(t)\sin\omega t_{est}$ is the signal estimated by the neural network (the active or reactive current). The difference between these two quantities corresponds to the error $e(k)$ used by to train the algorithm to update the weights of the ADALINE. To carry out a fine prediction of the signal, the algorithm minimizes the average square error between actual and estimated signals. The Widrow-Hoff learning rule is given in [6]. To make the algorithm faster and to reduce the convergence problems, a modified weight adaptation law [2] is used, according to:

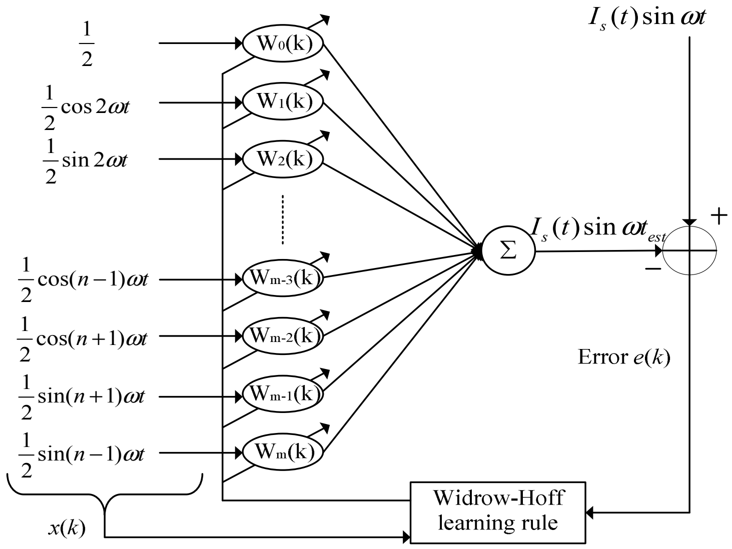

Fig. 1: The architecture of an ADALINE network

$$W(k+1) = \begin{cases} W(k) + \dfrac{\mu e(k) y(k)}{x^T(k) y(k)}, & \text{si } x^T(k) y(k) \neq 0 \\ W(k) & \text{si } x^T(k) y(k) = 0 \end{cases}, \qquad (7)$$

$$y(k) = 0.5\,\mathrm{sgn}(x(k)) + 0.5x(k)\,, \qquad (8)$$

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

The inputs are sinusoidal signals, therefore $|y(k)| \geq |x(k)|$, which leads to faster convergence. That constitutes a modified version of the algorithm and we will use it in our simulations.

The amplitude of the continuous component of the fundamental active current will be determined by the weight $W_0(k)$ of a first neural network ADALINE. The continues component of the reactive current will be also calculated by the weight $W_0(k)$, but of a second neural network ADALINE. We can then reconstitute the fundamental current by multiplying respectively I_{11} and I_{12} by $\cos\omega t$ and $\sin\omega t$:

$$I_{sf}(t) = I_{11}\cos\omega t + I_{12}\sin\omega t\,. \qquad (9)$$

The harmonics current are given by the relation: $I_{sh}(t) = I_s(t) - I_{sf}(t)$.

The complete scheme of the fundamental current estimation $I_{sf}(t)$ and the harmonics current $I_{sh}(t)$ of one phase is represented on figure 2.

These harmonics currents will be injected thereafter in opposition phase in the low-voltage power systems via a control device. The source current is made now sinusoidal and without charge from harmonics.

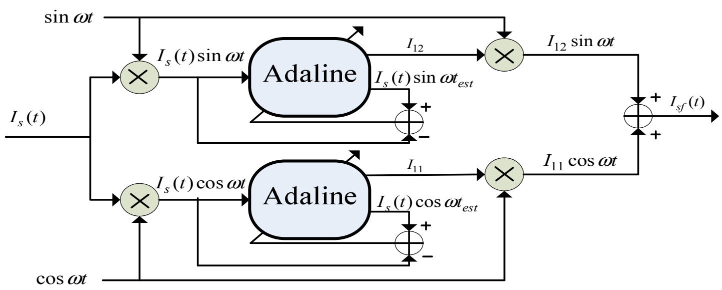

Fig. 2: Scheme of the fundamental current

4 Simulations results

To evaluate the proposed approach, a practical case which is representative of the most common power quality environment, was created mathematically and simulated in Matlab-Simulink. In the considered power system, the three-phase source has the following characteristics: $R_s = 1{,}269$ mΩ, $L_s = 46{,}49$ µH, $V_s = 230$ V and $f = 50$Hz. In order to create harmonic distortions, a nonlinear load (a Graetz bridge with RL branches) has been introduced, with the following parameters: 100 kVA, $\alpha = 0$, $R_c = 5$ mΩ, $L_c = 400$ µH.

By considering the fundamental current and the harmonics of row 3, 5, 7 and 11, each of the two ADALINE will have 19 inputs. The choice of the training parameter μ is very significant. A high value of μ allows a fast convergence but an inadequate estimation of the continuous components. A low value of μ gives an excellent estimation of the continuous components but with a slower convergence. In order to make a compromise between convergence and component estimation, we start with an elevate value of μ and we reduce it linearly until a fixed small value during the training.

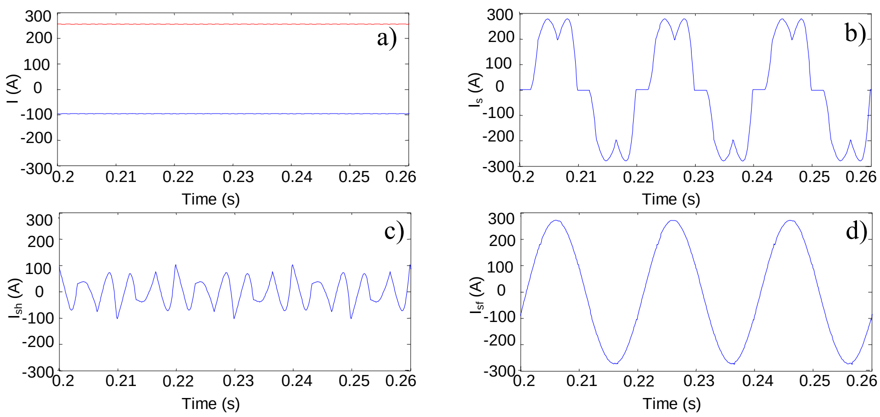

Fig. 3: The compensation results. a) Direct components of active and reactive current, b) Load current, c) Reference current, d) source current after compensation.

The estimated active and reactive fundamental currents delivered respectively by the two ADALINE are given by the figure 3a. Furthermore, the addition of the active and reactive alternative components enables us to realize the references currents (figure 3b). The figure 3c shows the charge current measured on the phase 1, and the figure 3d gives the source current after compensation.

To compare our results with those obtained by the traditional methods, we conserved an identical control device. For a traditional approach, the best results are limited to a rate of 1.2% of the THD (Total Harmonic Distortion). The use of the neural approach with the IARP method reduces the THD under a level of 0.9%. With our new decomposition suited to single-phase and three-phase systems, the THD is still reduced to 0.79%.
Other simulations show that the method, with the new decomposition we introduced, favourably compares to other methods like conventional methods, the methods proposed in [2].

5 Conclusion

The objectives of our work consist in improving the performances of the parallel APF. We used neural networks with on line learning for the identification of harmonic currents. An original decomposition of signals from an electrical network made it possible to determine the inputs of two ADALINE in charge of the reference currents estimation. A modification of the Widrow-Hoff algorithm allowed a fast convergence of the network weights.

The performances reached by the suggested method are better than those obtained by more traditional techniques. Moreover, our method is suited to single-phase and three-phase systems and makes it possible, if necessary, to extract the harmonics individually. Based exclusively on neural networks, our strategy leads to a homogeneous computation structure well adapted to a hardware target and real time processing.

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