Artificial Neural Networks for Harmonic Estimation in Low-Voltage Power Systems

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ABSTRACT

Harmonic estimation is the foundation of every active noise canceling method in low-voltage power systems. Reference currents are generated and re-injected in phase opposition through an active power line conditioner. Active Power Filters (APFs) are today the most widely used systems to compensate harmonics in industrial power plants. We propose to improve the performances of conventional APFs by using artificial neural networks (ANNs) for harmonics estimation. This new method combines both the advantages of conventional APF to compute instantaneous real and imaginary powers and the learning capabilities of ANNs to adaptively choose the parameters of the power system. In fact, the separation of the powers is implemented with an Adaline neural network which uses *a priori* known frequencies as inputs. Furthermore, multilayer feedforward networks are used to approximate the instantaneous powers and to compute the reference currents. Simulation results show the reliability of the method and better performances than conventional APFs.

I. INTRODUCTION

Due to the increasing presence of loads absorbing non sinusoidal currents such as regulators, motors, etc., harmonic distortions have become a significant issue for power consumers. These distorsions may have damaging effects on the equipment.

Active Power Filters (APFs) are proposed to compensate harmonics in existing power systems [1]. APFs are able to correct the power factor without any additional equipment.

Rigorous identification of harmonics is crucial in terms of current compensation performances and several methods have been developed in recent years. For example, Kalman filters have been applied with the need for a dynamic state model [2] . The Fast Fourier Transform (FFT), which needs a lot of computation resources [3], has also been applied. More recently, artificial neural networks (ANNs) have been introduced as a complement or an alternative to conventional methods [4]. ANNs have been associated with the Park vectors representation [5] and can be used with a direct measure of the current [6].

Our method uses ANNs to compute the instantaneous real and imaginary powers as described in [1] allowing thus a precise selection of the harmonics. The proposed method replaces the conventional Concordia transformations (direct and inverse) and the computation of the instantaneous real and imaginary powers, with multilayer feedforward networks. The harmonics identification itself is implemented with an Adaline neural network.

We introduce ANNs in harmonic estimation methods by considering two aims. Firstly, the adaptability of ANNs must lead to similar or better performances than conventional methods for varying loads. Secondly, the structure must be suited for hardware implementation.

The computation of the instantaneous real and imaginary powers is presented in Section II. Section III introduces the ANNs for voltage and current wave forms estimation. The application of the proposed method is demonstrated in Section IV. Finally, Section V concludes the paper.

II. COMPUTING THE INSTANTANEOUS REAL AND IMAGINARY POWERS

The principle of harmonic compensation in power systems is shown in Fig. 1. The presence of the nonlinear load introduces harmonics distortions in the source current I_S and transforms it in a load current I_L. The APF has to identify the harmonics distortions to restore the initial form of the current.

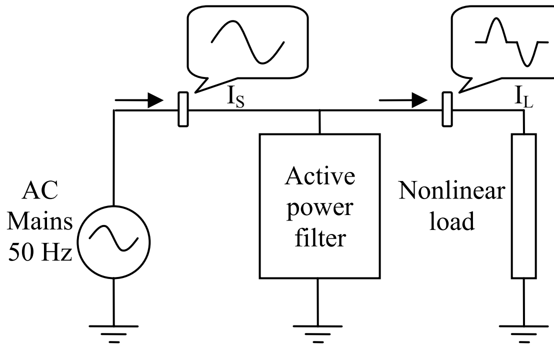

Figure 1. The APF's principle in a power system

Active power compensation schemes have two main parts: the first one generates the reference signals and the second one carries out the control signals. The identification strategy is decomposed in several blocks as detailed by Fig. 2.

At first, we introduce a phase-locked-loop (PLL) to allow the computation of the instantaneous real and imaginary powers, whatever the environment, condition or load [1]. Indeed, the instantaneous real and imaginary powers computation is only possible if the input of the identifier is a phase-equilibrated system where voltage waveforms are sinusoids.

The next step consists in transforming the phase voltages and load currents into an α – β orthogonal coordinates system according to the Direct Concordia Transformation (DCT). This transformation, from a three-phase system to a two-phase system, simplifies the mathematical expressions and reduces the computational costs:

$$\begin{bmatrix} V_0 \\ V_\alpha \\ V_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} . \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & \frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ V_3 \end{bmatrix}, \qquad (1)$$

$$\begin{bmatrix} I_0 \\ I_\alpha \\ I_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} . \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & \frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} I_{S1} \\ I_{S2} \\ I_{S3} \end{bmatrix}. \qquad (2)$$

Instantaneous active and reactive powers, respectively p and q, are then calculated as:

$$\begin{bmatrix} p \\ q \end{bmatrix} = \begin{bmatrix} V_\alpha & V_\beta \\ -V_\beta & V_\alpha \end{bmatrix} . \begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix}. \qquad (3)$$

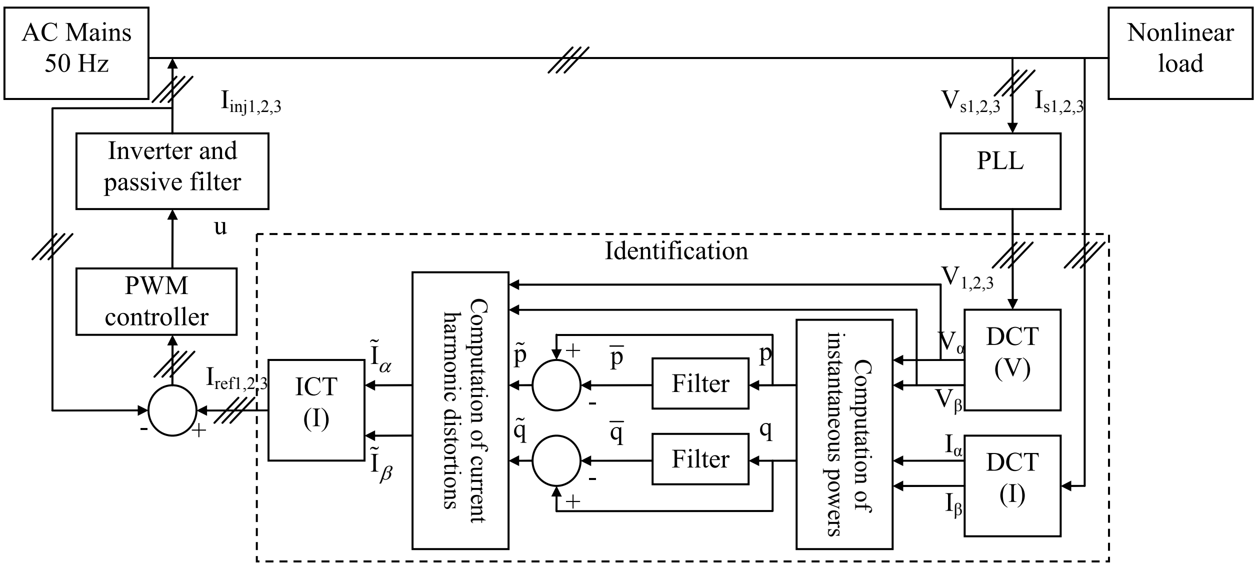

Figure 2. The AFP's general structure

Instantaneous active and reactive powers can be decomposed into DC components $\bar{p}$ and $\bar{q}$ related to the fundamental frequency and into AC components $\tilde{p}$ and $\tilde{q}$ which represents the terms produced by the harmonic distortions. Thus, $p = \bar{p} + \tilde{p}$ and $q = \bar{q} + \tilde{q}$.

Filters are used to separate the terms produced by the harmonic distortion from the DC components related to the fundamental frequency. The terms $\tilde{p}$ and $\tilde{q}$ are thus rejected. Inverting (3) using the instantaneous powers $p = \bar{p} + \tilde{p}$ and $q = \bar{q} + \tilde{q}$ leads to:

$$\begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix} = \frac{1}{\Delta}\begin{bmatrix} V_{s\alpha} & -V_{s\beta} \\ V_{s\beta} & V_{s\alpha} \end{bmatrix}\begin{bmatrix} \bar{p} \\ 0 \end{bmatrix} + \frac{1}{\Delta}\begin{bmatrix} V_{s\alpha} & -V_{s\beta} \\ V_{s\beta} & V_{s\alpha} \end{bmatrix}\begin{bmatrix} 0 \\ \bar{q} \end{bmatrix} + \frac{1}{\Delta}\begin{bmatrix} V_{s\alpha} & -V_{s\beta} \\ V_{s\beta} & V_{s\alpha} \end{bmatrix}\begin{bmatrix} \tilde{p} \\ \tilde{q} \end{bmatrix} \quad ,(4)$$

where $\Delta = V^2{}_{s\alpha} + V^2{}_{s\beta}$.

The harmonic distortion for the currents in the α – β orthogonal coordinates can be identified as

$$\begin{bmatrix} \tilde{I}_\alpha \\ \tilde{I}_\beta \end{bmatrix} = \frac{1}{\Delta}\begin{bmatrix} V_{s\alpha} & -V_{s\beta} \\ V_{s\beta} & V_{s\alpha} \end{bmatrix}\begin{bmatrix} \tilde{p} \\ \tilde{q} \end{bmatrix}, \qquad (5)$$

and the following currents can be determined with the Inverse Concordia Transform (ICT):

$$\begin{bmatrix} I_{ref1} \\ I_{ref2} \\ I_{ref3} \end{bmatrix} = \sqrt{\frac{2}{3}}\begin{bmatrix} 1 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix}\begin{bmatrix} \tilde{I}_{p\alpha} \\ \tilde{I}_{p\beta} \end{bmatrix}. \qquad (6)$$

These currents serve as reference currents and are injected equal but opposite into the power plant through the Pulse Width Modulation (PWM) controller, thereby canceling the original distortions.

III. NEURAL NETWORKS FOR VOLTAGE AND CURRENT WAVEFORMS ESTIMATION

This work proposes a new approach based on the application of ANNs to the estimation of the magnitude of the symmetrical components of individual harmonics. The structure of APFs is kept but each block is replaced by ANNs as shown by Fig. 3. Its advantage is that the ANNs estimate the reference currents from direct measurements of the currents and voltages.

Principle of compensation currents

The phase voltages into α – β orthogonal coordinates and the instantaneous active and reactive powers are now approximated with the use of two multilayer feedforward networks (block 1) which replace Eq. (1) to (3). An Adaline (block 2) identifies and separates the AC components $\tilde{p}$ and $\tilde{q}$ from the DC components $\bar{p}$ and $\bar{q}$. This Adaline takes *a priori* frequencies as inputs and the filter delivers two outputs, estimating the powers due to the harmonic distortions. The signals $\tilde{p}$ and $\tilde{q}$, combined with the voltages V_α and V_β are then converted into reference currents. This transformation, previously given by Eq. (6), is implemented with a multilayer feedforward network (block 3). The benefit of this method over other conventional identifiers used in APFs is that it is based on instantaneous power computation. Power signals allow to estimate only one continuous component rather than several alternative components which is more difficult.

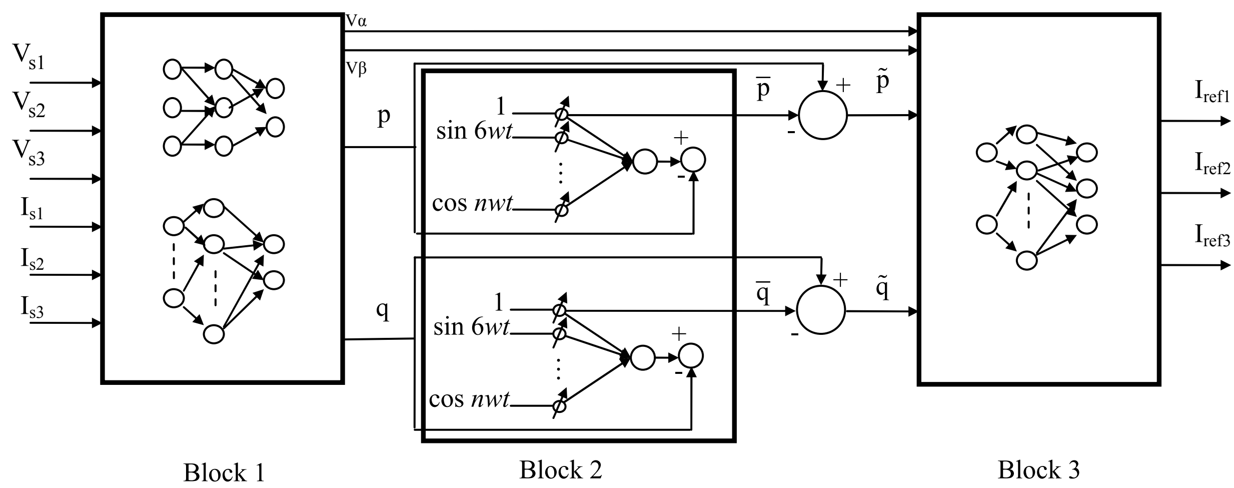

Figure 3. Neural network identifier

The implementation of the transformations with feedforward ANN before and after the filtering are presented in [7]. In this paper, we focus on the filtering and harmonic estimation stages.

Adaline for harmonic estimation

The Adaline is a simple dynamical learning system by means of a linear combination of time-dependent signals. Introduced by Widrow [8] with the LMS (Least Mean Square) learning rule, the Adaline is now widely used in signal processing theory for signal estimation and prediction. Recently, it has emerged as a new harmonic estimation technique [6, 9]. We will use this principle and introduce *a priori* frequency knowledge to identify the harmonic distortions. Based on an Adaline, the compensation scheme can then adapt itself to changes to any load current waveform.

As nonlinear loads are present in a power plant, load current waveforms are nonsinusoidal. Every periodic waveform can be expanded by Fourier analysis as a sum of cosine and sine frequency components. Thus, load voltages and currents can be expressed as follows:

$$I_L(t) = \sum_{n=1,\ldots,N} I_{n1} \cos n(\omega t - \beta) + I_{n2} \sin n(\omega t - \beta) \;, \quad (7)$$

$$V_L(t) = \sum_{n=1,\ldots,N} V_{n1} \cos n\omega t + V_{n2} \sin n\omega t \;, \quad (8)$$

with ω the fundamental frequency, β the conduction angle of the thyristors, V_{n1} and V_{n2} the cosine and sine frequency components of load voltages, and I_{n1} and I_{n2} the cosine and sine frequency components of the load currents.

The frequency analysis of the instantaneous active and reactive powers gives:

$$p(t) = \underbrace{p_1 \cos\beta}_{\bar{p}} + \underbrace{p_5 \cos(6\omega t - 5\beta) - p_7 \cos(6\omega t - 7\beta) - \cdots}_{\tilde{p}} \;, \quad (9)$$

$$q(t) = \underbrace{-q_1 \sin\beta}_{\bar{q}} - \underbrace{q_5 \sin(6\omega t - 5\beta) - q_7 \sin(6\omega t - 7\beta) + \cdots}_{\tilde{q}} \;, \quad (10)$$

In Eq. (9) and (10), $p_1 \cos\beta$ and $-q_1 \sin\beta$ represent the DC components, respectively $\bar{p}$ and $\bar{q}$. The other terms contribute to the AC components $\tilde{p}$ and $\tilde{q}$.

Both signals given in Eq. (9) and (10) can be written in the following discrete general form:

$$f(t) = A_0 + \sum_{n=1,\ldots,N} \begin{pmatrix} A_n \cos\left(n\omega t - (n-1)\beta\right) \\ +A_n \cos\left(n\omega t - (n+1)\beta\right) \\ +B_n \sin\left(n\omega t - (n-1)\beta\right) \\ +B_n \sin\left(n\omega t - (n+1)\beta\right) \end{pmatrix}, \quad (11)$$

where A_0, A_n and B_n are the amplitude of the cosine and sine components of the $n-$order harmonic.

Function $f(t)$ is introduced in (11) is a linear combination. The principle and the structure of the Adaline is thus well suited to compute an estimation $f_{est}(t)$ of $f(t)$.

Expression (11) gives, in vectorial notation:

$$f_{est}(t) = W^T . x(t) \;, \quad (12)$$

where $W^T = [A_0 A_1 B_1 \cdots A_N B_N]$ is the Adaline weight vector, and

$$x(t) = \begin{bmatrix} 1 \\ \cos(6\omega t - 5\beta) \\ \sin(6\omega t - 5\beta) \\ \cos(6\omega t - 7\beta) \\ \sin(6\omega t - 7\beta) \\ \vdots \\ \cos(n\omega t - (n-1)\beta) \\ \sin(n\omega t - (n-1)\beta) \\ \cos(n\omega t - (n+1)\beta) \\ \sin(n\omega t - (n+1)\beta) \end{bmatrix} \quad (13)$$

the network input vector composed of the cosine and sine components of the $n-$order harmonics. 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 results in an estimated signal composed of different harmonics.

In this structure, the bias term of the Adaline represents the importance (scale) of the constant component of the input vector $x(t)$ and thus allows to learn and estimate the DC component of $f(t)$. Obviously, the other weights represent the contribution of the different AC components of $f(t)$.

Furthermore, the Adaline structure can be optimized. For example, if a load introduces some well known harmonics distortions, the corresponding generated

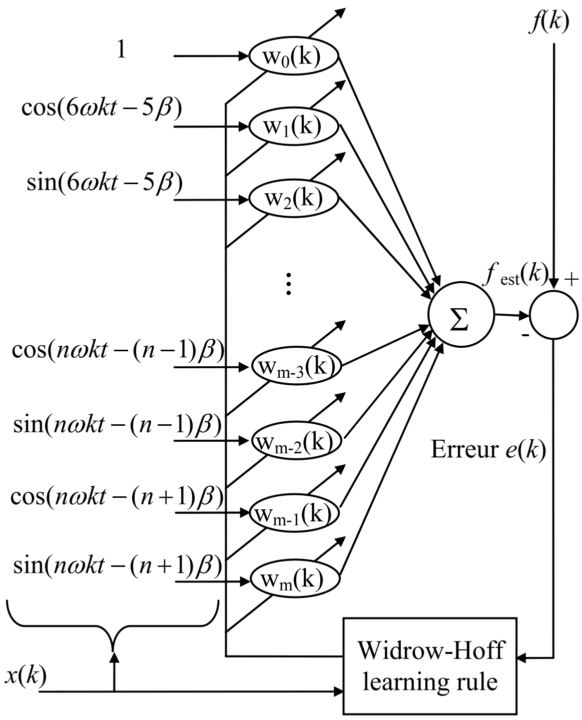

Figure 4. The architecture of an Adaline network

cosine and sine components of the input vector can be adjusted consequently (with parameters n, α, and m).

The product presented in Eq. (12) gives one output. In our application, we need two outputs to identify and separate the harmonics from the DC components, one for the instantaneous active power and one for the instantaneous reactive power.

The general architecture of the Adaline with the generated sinusoidal signals is presented by Fig. 4. The signals are sampled with uniform rate (1 µs period), thus, time values are discrete with $k = 0,1,2...$ The input vector $x(k)$ contains $m = h/2-1$ terms, where h represents the number of harmonics that must be identified.

The Widrow-Hoff learning rule can be written as follows:

$$W(k+1) = W(k) + \frac{\alpha e(k)x(k)}{x^T(k)x(k)}, \qquad (14)$$

In (14), the error is the difference between the actual signal $f(k)$ and its estimation $f_{est}(k)$ at time step k. α is the learning rate.

We use a modified Widrow-Hoff learning rule, which minimizes the average square error between actual and estimated signals, respectively $f(k)$ and $f_{est}(k)$. To make the algorithm faster and to reduce the convergence problems, a modification is introduced in the weight adaptation law:

$$W(k+1) = \begin{cases} W(k) + \dfrac{\alpha e(k)y(k)}{x^T(k)y(k)} & \text{if } x^T(k)y(k) \neq 0 \\ W(k) & \text{if } x^T(k)y(k) = 0 \end{cases}, \qquad (15)$$

with

$$y(k) = 0.5\,\text{sgn}(x(k)) + 0.5x(k)\,. \qquad (16)$$

The inputs are sinusoidal signals, therefore $|y(k)| \geq |x(k)|$, which leads to faster convergence.

IV. SIMULATION RESULTS

To check the proposed approach, a practical case, 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, $V_{s1,2,3} = 230$ 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.

Besides the three-phase sinusoidal source and the nonlinear load, a model of a three-phase AC regulator and a compensation structure is inserted into the power system.

The performances of the neural compensation technique will be compared to those of a conventional APF in the same application.

Fig. 5 shows the estimated instantaneous active powers at each sample time and its estimated direct component. The Adaline uses a bias term to learn and estimate the DC component of the instantaneous active power. The difference between these two signals represents the alternative component of the active power and will serve to calculate the reference currents. The same principle is applied for the estimation of the DC component of the instantaneous reactive power represented by Fig. 5.

The estimation error of the DC components is 0.01 %, which is acceptable for powers signals. This results in more accurate estimations of AC components of the instantaneous powers. The AC components of the active and reactive powers are then converted into reference currents through block 3 (Fig. 3). The reference currents

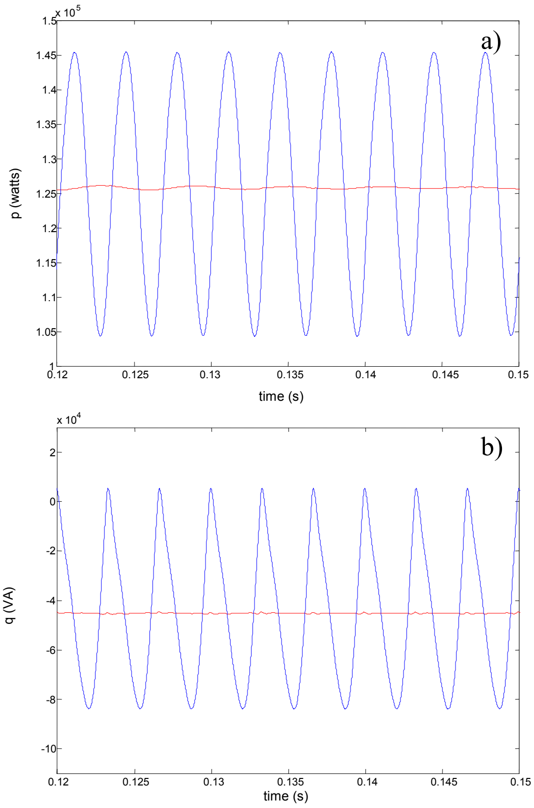

Figure 5. Estimated instantaneous active and reactive power and the corresponding DC component

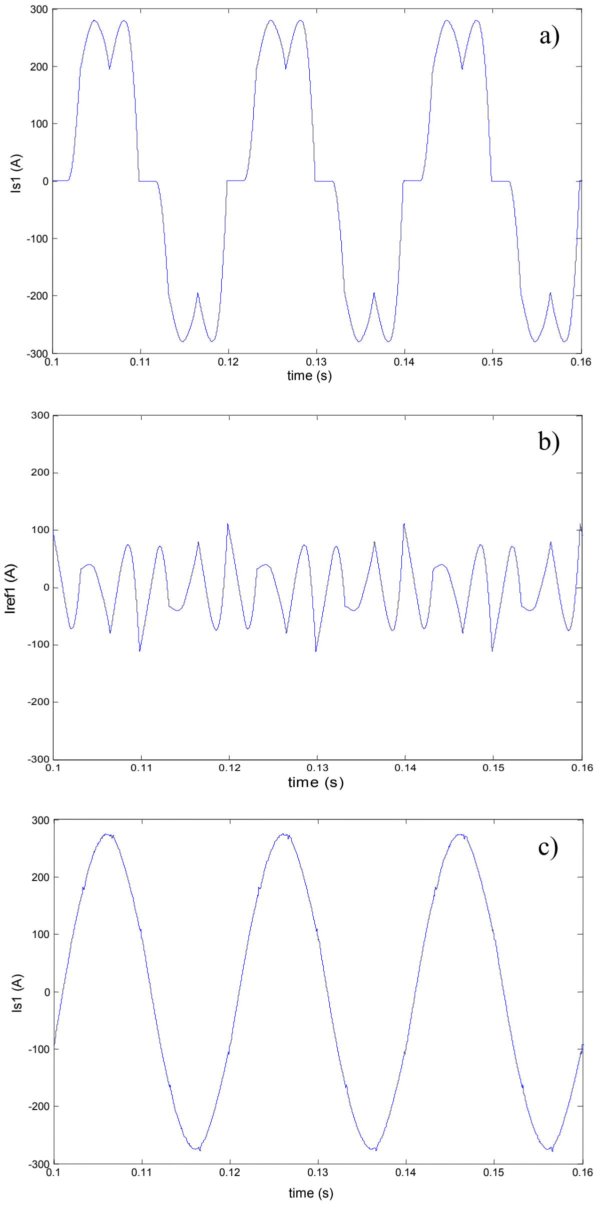

Figure 6. For the first phase, a) the source and load current before application of the compensation, b) the reference current, and c) source current after the application of the compensation with the ANNs approach

are equal but opposite of the distortions, and are injected in the power plant, therefore canceling the original distortions and improving power quality on the connected distribution system. The performances of the proposed technique with the ANNs approach are given in Fig. 6. The waveform of the measured source and load current without any compensation technique is shown first in Fig. 6a. The reference current resulting from the compensation with the ANNs approach, and the source current after the application of the compensation are presented in Fig. 6b-c. The reference currents issued from the proposed compensation technique cancel the harmonics generated by the nonlinear load and thus result in a sinusoidal current without harmonics distortions.

The Total Harmonic Distortion (THD) parameter, calculated without and with conventional active power filter, is reduced from 24,2 % to 1,2 %. The THD parameter is reduced to 0,85 % after the neural estimated compensation currents are applied. Therefore, there is a better reduction in harmonic distortion with the neural compensation technique than with the conventional APF.

V. CONCLUSION

The focus of this paper is to improve the compensation performance of the conventional APF by identifying the active and reactive powers to cancel the harmonic distortions due to nonlinear loads in electric power plants. We proposed a new identification approach based on ANNs. Its computational requirements correspond to a homogeneous structure allowing a different hardware implementation.

The neural compensation technique is designed to estimate the active and reactive power harmonic components. Thus, it consists of the application of the Park vector theory to the unbalanced three-phase system analysis. The conventional Concordia transformations (direct and inverse) are implemented with multilayer feedforward networks. The harmonic identification is done with the instantaneous active and reactive powers through an Adaline neural network. Based on *a priori* knowledge, the Adaline estimates and accurately separates the instantaneous active and reactive powers into AC components and DC components. The estimated AC components are used to generate reference currents to cancel the unwanted harmonics.

The neural compensation technique was applied to a nonlinear unbalanced three-phase system and was compared to a conventional APF. The results allow concluding that the neural compensation technique is better than the conventional APF for the determination of the harmonic components and for the reduction of harmonic distortions.

The main advantage of the proposed technique is its ability to adapt to varying loads in real time. The compensation structure is modular, composed of different blocks of homogeneous neural networks, and can thus be used as basis for more general architectures, and especially for hardware implementation.

VI. ACKNOWLEDGEMENTS

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