

A Complete Neuromimetic Strategy for Harmonics Identification and Control of a Three-Phase Voltage Inverter used for the Power Active Filtering

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Abstract: Only based on the use of neural techniques: Artificial Neural Networks (ANNs), This paper presents a complete neural strategy for harmonics identification and control of a three-phase voltage inverter used for the power active filtering (APF), so our main motivation is to build a neural APF. This approach of compensation is done in three neural blocks. In The first one we propose a new neural approach based on Adalines for the online extraction of the symmetrical voltage components, i.e., Phase-Locked Loop (PLL) based on the Instantaneous Powers Theory (IPT), to recover a balanced and equilibrated voltage system. The second block extracts the harmonic currents with synchronized method by using Adaline neural networks. The third block injects the harmonic currents with opposite phase in the electrical supply network; it uses a PI-neural controller to control the inverter. To maintain the dc voltage capacitor constant and compensate the inverter losses a neural proportional integral voltage controller is used. By their learning capabilities of ANNs, our approach is automatically able to adapt itself to any change of the non-linear and thus appreciably improve the performance of traditional compensating methods. Furthermore, The proposed neural compensation approach has been evaluated in simulations. The results show excellent behaviors and performance, as well as robustness and usefulness in terms of total harmonic THD distortion and power factor PF under various operating conditions.

Key words: Active power filter (APF), Artificial Neural Networks (ANNs), PI-neural controller, neural synchronous method, power quality.

1. Introduction

Nowadays, harmonic distortions generated by nonlinear loads which are more and more present in industrial and domestic electric installations. is becoming so serious, that the quality of the public supply is barely acceptable. due to time-varying non-linear loads such as rectifiers, variable speed transmissions, AC regulator, lighting, etc. Indeed, those nonlinear loads absorb non sinusoidal currents generating thus harmonics components and unbalanced voltages in the whole power system. Further, low frequency harmonics (5th, 7th ... harmonics) should be suppressed because they can excite resonance in the electric network and cause mechanical stress and additional heating [1].

For several years, Active Power Filters (APFs) have been recognized as advanced techniques for harmonic compensation in power distribution networks [2, 3]. Their objective is to recover balanced and sinusoidal source currents by injecting compensation currents. APFs are very able to suppress the current harmonics and to compensate for the power factor, especially with fast-fluctuating loads, in comparison to other compensation devices. Thus, An APF is generally used to ensure a constant active power in the distribution system but also sinusoidal waveforms of the source currents [4].

Since a few years, Artificial Neural Networks (ANNs) techniques have been applied with success in the control of APFs and are very promising in the field. Indeed, the learning capacities of the ANNs allow an on-line adaptation to every changing parameters of the electrical network, e.g., nonlinear and time-varying loads [5]. Inserted in an APF scheme, they can appreciably improve its performance compared to the one obtained with traditional compensating methods [3].

In this paper, an APF system only based on ANNs is proposed. The neural APF is composed of three parts that work independently. Each part, the online extract the direct and inverse voltage components (PLL-neural), the filtering of the harmonics and the control of the APF's power circuit, are based on a unique and a simple type of ANN: the Adaline Neural Network.

A neural method for harmonic identification and compensation was studied, i.e the synchronized method. In this harmonic compensation method, the disturbed currents were decomposed in a linear expression. Using an on-line learning, the Adalines are thus able to approximate this expression and can thus estimate each harmonic component. The control of the inverter is carried out by a PI-neural controller able to adapt to every changing parameters of the electrical network. This control scheme shows the principle of a PI controller and employs an Adaline network to adjust the parameters proportional and integral [1].

The PLL proposed in this paper is also based on the IPT of [6]. This approach has been derived leading

in a new formulation of the instantaneous powers which has been learned by an Adaline neural networks [7] followed by a phase detection based on an proposed VCO which inserted a PI-neural regulator.

The performances of the proposed neural shunt active filter based on Adalines are evaluated using MATLAB-Simulink and power system Block Set Toolbox under unbalanced voltage conditions. The Total Harmonic Distortion (THD) and the Power Factor (PF) are therefore calculated and analyzed. The obtained results show that the APF-neural with the Adaline-based schemes is able to adapt itself to the variations of the nonlinear load currents.

2. APF for harmonic compensation

2.1. Principle of Shunt Active Filter

Nowadays, among all APF's topologies, the shunt APF is the most widely used in industrial sites. It can be considered as the most basic configuration of APF, and includes the main critical issues associated with APF control [2, 3]. The APF's rule consists in identifying all the present harmonic components and to separate the fundamental component from other harmonic components which are converted in resulting reference currents. A control strategy uses these reference currents to inject them in real-time into the utility source with opposite phase through a power circuit, i.e., an inverter and an output filter. This principle is showed in Fig.1.

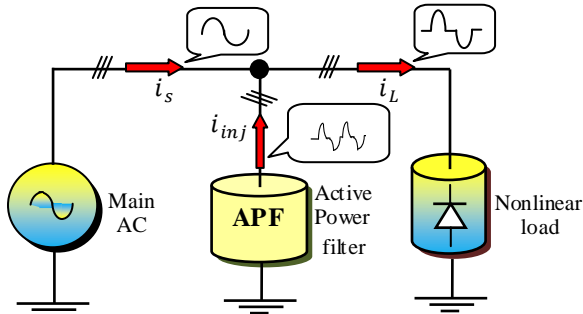


Fig. 1. Basic configuration of a shunt active filter.

2.2. Neural Architecture for APF

The architecture of the APF-neural can be decomposed in three blocks detailed as shown in Fig.2. In the first block, Adalines are used to online extract the direct and inverse voltage components from the composite voltage, and thus to determine the sinusoidal and equilibrated voltages required by some harmonic detection algorithms. a neural method, based on a specific decomposition of the currents are proposed for the second block which identifies the harmonic currents by Adalines. The learning algorithm, thus, determines the compensation currents from the identified distortion harmonics. The third block uses Adalines to control

the inverter of the APF in order to properly inject the compensation currents.

3. The Adaline neural network

3.1 Architecture

Since a few years, Artificial Neural Networks (ANNs) techniques have been applied with success in the control of APFs [8].

The Adaline (ADAPtive LINEar NEuron) is basically a linear combiner that uses the LMS algorithm for its operation. Fig. 3 shows the general network topology of an Adaline, where X_k is an input vector of dimension n , W_k is an adjustable weight vector of dimension n , and y_k is the scalar output. Indeed, without loss of generality multiple outputs can be handled by multiple Adalines with the same input vector. The output of the Adaline can be calculated for any input X_k at sample time k as follow:

$$y_k = \sum_{i=1}^n X(i)_k W(i)_k = X_k^T W_k \quad (1)$$

This relationship between its input and output signals is linear at any given time, but because of its adaptive nature, the weights are adjusted on-line and are thus a function of time.

The major advantage of the Adaline is the ability to interpret its parameters, which is not generally the case of multilayer neural networks (MLP). The simplicity of its architecture is advantage when a hardware implementation is envisaged [9].

3.2 Learning rules

Widrow (and Walach, 1996) proposed the LMS algorithm, which has been extensively applied in adaptive signal processing and adaptive control [10, 11]. The Adaline network uses a supervised learning process, a desired output d_k is provided with each input $X(k)$ during the training. The LMS algorithm is based on the minimum mean squares error. The learning process uses this error to adjust the weights:

$$e_k = d_k - y_k = d_k - X_k^T W_k \quad (2)$$

The next weight vector W_{k+1} equals the present weight vector W_k plus a change ΔW based on the error e_k at sample time k .

$$W_{k+1} = W_k + \Delta W \quad (3)$$

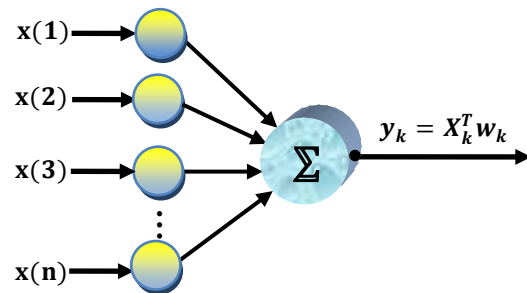


Fig. 3. The general network topology of an Adaline.

In our work, All Adalines weights are iteratively adapted with the Widrow-Hoff learning rule called

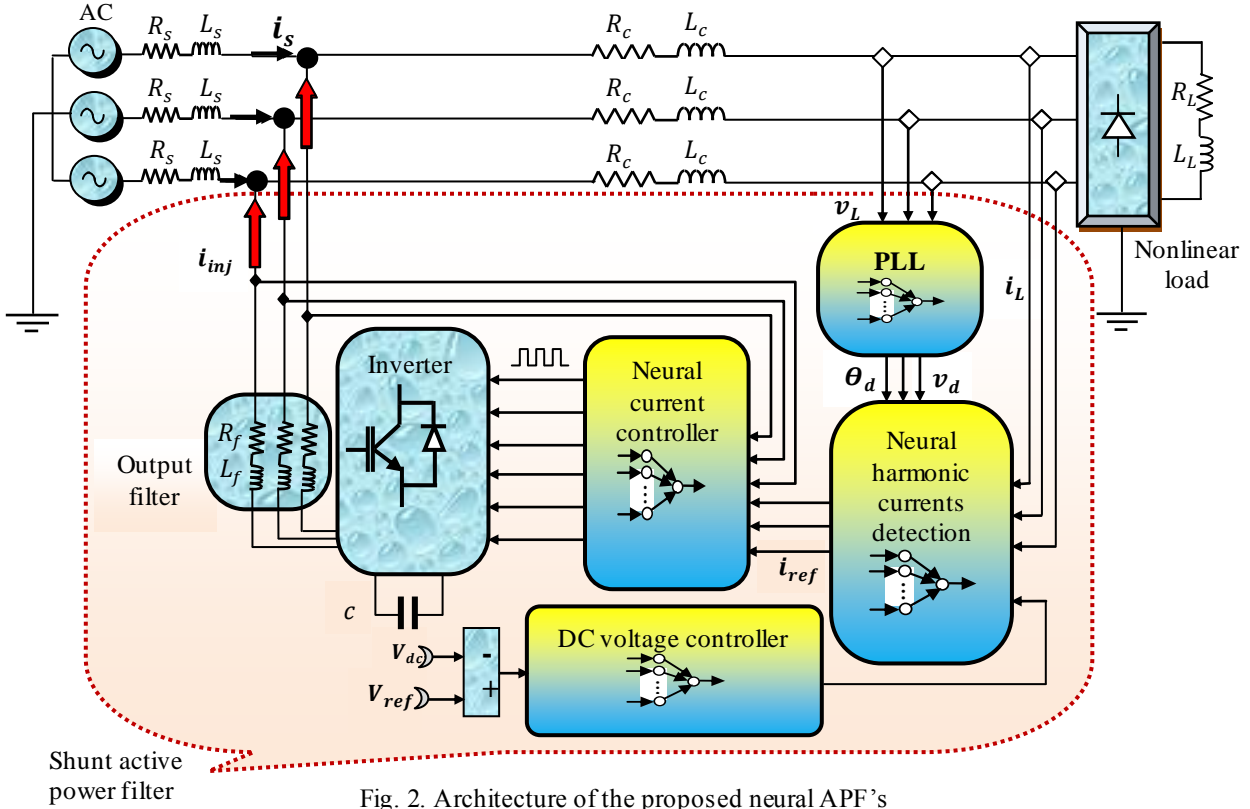


Fig. 2. Architecture of the proposed neural APF's

the μ -LMS learning rule (Least-Mean-Squares), which is given by:

$$\Delta W = \frac{\mu e_k X_k}{X_k^T X_k} \quad (4)$$

Where μ is the learning rate parameter $\mu \in [0,1]$.

4. Novel three-phase PLL-neural

In such applications, the excessive fluctuations of the signal parameters adversely affect the quality of the power in the distribution system, particularly in terms of frequency and voltage [6, 7].

Because, some of a neural harmonics identification schemes are sensitive to this frequency fluctuations, our APF is thus enhanced with a voltage component Extraction strategy (PLL-neural) and aim to be universal compensator able to cancel the harmonics currents, the reactive power and imbalances of the voltages and currents.

The proposed approach, illustrated by Fig. 4, is composed of two blocks: at first a symmetrical

voltage components extraction followed by a instantaneous phase detection algorithm. For each block, the expressions can be learned by Adaline neural networks. The whole approach is adaptive and able to take into account changing parameters.

4.1. Neural symmetrical components extraction method

A neural approach is proposed to extract the symmetrical components of the voltages of the power distribution system. This approach relies on a new formulation of the Instantaneous Powers Theory (IPT) which is learned by Adaline neural networks and is unbalanced conditions.

The principle of the symmetrical components extraction is based on the IPT (p - q theory) [6]. According to this theory, the pq -powers are calculated and their AC and DC-terms are instantaneously separated. Thence, the DC-terms are converted in the current reference frame as shown by Fig. 5 in order to compute the direct voltage components. In the IPT, the instantaneous powers are calculated from the $\alpha\beta$ -frame with [6, 12, 7, 13].

$$\begin{bmatrix} p \\ q \end{bmatrix} = \begin{bmatrix} v_\alpha & v_\beta \\ v_\beta & -v_\alpha \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} \quad (5)$$

The supply voltage in the $\alpha\beta$ -frame can be deduced :

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \frac{1}{i_\alpha^2 + i_\beta^2} \begin{bmatrix} i_\alpha & i_\beta \\ i_\beta & -i_\alpha \end{bmatrix} \begin{bmatrix} p \\ q \end{bmatrix} \quad (6)$$

Expression (6) is a general formulation that allows to determine the $\alpha\beta$ -voltages. This expression can

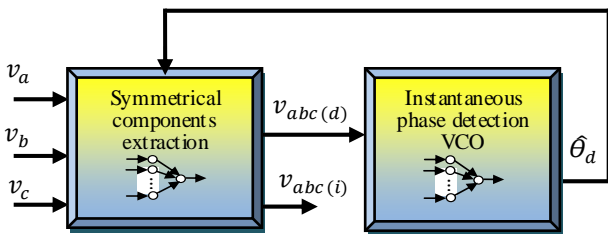


Fig. 4. Basic principle of the PLL-neural with phase detection.

be used to determine the fundamental direct voltage components by using currents issued from a direct fundamental system and DC-terms of the associated powers. Therefore:

$$\begin{bmatrix} v_{\alpha(d)} \\ v_{\beta(d)} \end{bmatrix} = \frac{1}{i'_{\alpha}{}^2 + i'_{\beta}{}^2} \begin{bmatrix} i'_{\alpha} & i'_{\beta} \\ i'_{\beta} & -i'_{\alpha} \end{bmatrix} \begin{bmatrix} \bar{p}' \\ \bar{q}' \end{bmatrix} \quad (7)$$

The auxiliary currents i'_{α} and i'_{β} correspond to the fundamental direct currents with an amplitude which is unit and a phase which is null in the $\alpha\beta$ -frame.

$$\begin{bmatrix} i'_{\alpha} \\ i'_{\beta} \end{bmatrix} = \begin{bmatrix} \cos\hat{\theta}_d \cdot I_d \\ \sin\hat{\theta}_d \cdot I_d \end{bmatrix} \text{ with } \dots I_d = 1 \quad (8)$$

These currents are also used to compute the fictitious powers p' and q' . These powers do not have a real physical meaning, they are based on the i'_{α} and i'_{β} currents and on the measured voltages v_{abc} :

$$\begin{bmatrix} p' \\ q' \end{bmatrix} = \begin{bmatrix} v_{\alpha} i'_{\alpha} & v_{\beta} i'_{\beta} \\ v_{\beta} i'_{\alpha} & -v_{\alpha} i'_{\beta} \end{bmatrix} \quad (9)$$

With $[v_{\alpha} \ v_{\beta}]^T = \sqrt{2/3} C_{32}^T v_{abc} = T_{32}^T v_{abc}$, the fictitious active power can be detailed as follows:

$$p' = \bar{p}' + \hat{p}' = \sum_{n=1}^N 3V_{in} I_d \cos(\phi_{n(d)} - \theta_d) + n=1N3Vin I_d \cos(\phi_{n(i)} + \theta_d)$$

$$\begin{aligned} p' &= v_{\alpha} i'_{\alpha} + v_{\beta} i'_{\beta} \\ &= \sum_{n=1}^N [\cos(n-1)\theta_d \quad \sin(n-1)\theta_d] \begin{bmatrix} 3V_{dn} \cos\phi_{n(d)} \\ -3V_{dn} \sin\phi_{n(d)} \end{bmatrix} \\ &+ \sum_{n=1}^N [\cos(n+1)\theta_d \quad \sin(n+1)\theta_d] \begin{bmatrix} -3V_{dn} \cos\phi_{n(d)} \\ 3V_{dn} \sin\phi_{n(d)} \end{bmatrix} \end{aligned} \quad (10)$$

Expression (10) is a sum of harmonic components which can be rewritten with a linearly separable equation:

$$y(k) = W^T X(k) \quad (11)$$

with

$$X(t) = \begin{bmatrix} \cos(n-1)\theta_d \\ \sin(n-1)\theta_d \\ \cos(n+1)\theta_d \\ \sin(n+1)\theta_d \end{bmatrix}; \quad W = \begin{bmatrix} 3V_{dn} \cos\phi_{n(d)} \\ -3V_{dn} \sin\phi_{n(d)} \\ -3V_{in} \cos\phi_{n(i)} \\ 3V_{in} \sin\phi_{n(i)} \end{bmatrix} \quad (12)$$

Expression (10) is learned and approximated by an Adaline neural network. This Adaline is based on a supervised learning; its output $y(k)$ is compared to an example, i.e., a desired value which is p' obtained with the fictitious currents and the measured voltages v_{abc} when learning (10). The error $e = p' - y$ is used by an optimal LMS (Least Mean Square) learning algorithm to correct the Adaline weights w for the next sampling time. Under these conditions, the Adaline weights w are enforced to converge. After training, the elements of w represent Power amplitudes resulting from the direct voltages at frequency $n\omega$ and the currents given by (8).

Finally, the fundamental direct voltages $v_{abc(d)}$ of the three-phase system is obtained by using the first two elements of the weight vector. Indeed, w_0 and w_1 correspond to the fundamental component ($n = 1$) and represent respectively the DC-parts of the instantaneous powers \bar{p}' and \bar{q}' . The voltage $v_{abc(d)}$ are recovered by converting these continuous powers in the $\alpha\beta$ -voltage space with (7) and by multiplying them with the Concordia transform T_{32} .

The fictitious reactive power q' is developed with the same principle by using the currents defined in (13). The resulting expression is learned by an Adaline and the fundamental inverse voltage components $v_{abc(i)}$ can be deduced from its two first weights.

$$\begin{bmatrix} i'_{\alpha} \\ i'_{\beta} \end{bmatrix} = \begin{bmatrix} \cos\hat{\theta}_d \\ -\sin\hat{\theta}_d \end{bmatrix} \quad (13)$$

The fundamental direct and inverse voltage components $v_{abc(d)}$ and $v_{abc(i)}$ can be used to deduced the zero-sequence voltage components $v_{abc(0)}$. They can also be used by a phase detection algorithm in order to estimate the frequency of the power system in real-time.

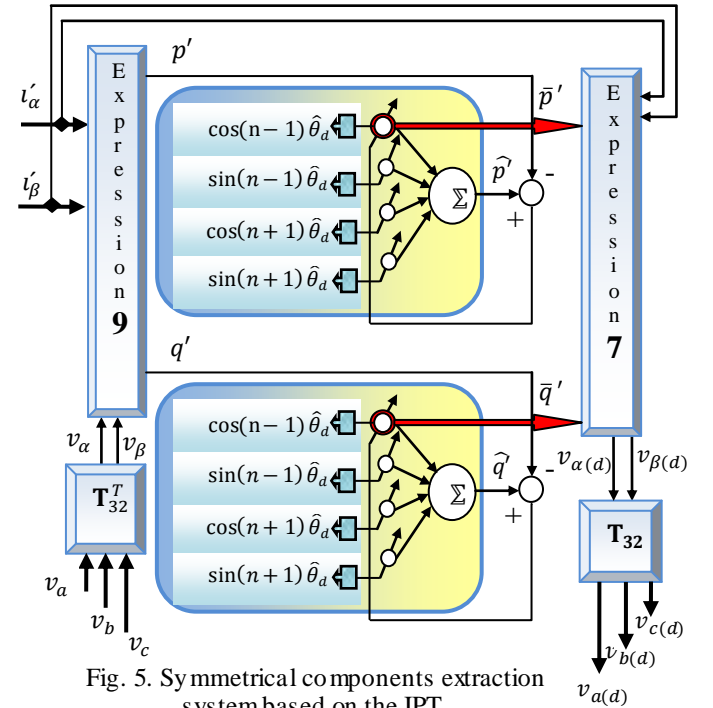


Fig. 5. Symmetrical components extraction system based on the IPT.

4.2. Proposed VCO (instantaneous phase detection)

In [12, 7, 13], an alternative solution that is an enhanced instantaneous phase detection algorithm which can be applied to all unbalanced disturbed three-phase system. It can be applied to every generic input signal, i.e., either voltages or currents issued from a three-phase system. Like a single phase VCO (Voltage Controlled Oscillator), the

proposed approach tries to keep the term $\sin(\theta_d - \hat{\theta}_d)$ close to zero, where θ_d is the phase angle of the system and $\hat{\theta}_d$ its estimation. The development of this term leads to:

$$\sin(\theta_d - \hat{\theta}_d) = \sin\theta_d \cos\hat{\theta}_d - \cos\theta_d \sin\hat{\theta}_d \quad (14)$$

Where, the term $\cos\theta_d$ can be associated to v_a , the fundamental voltage of phase a , and $\sin\theta_d$ can be associated to the voltage $v_{bc}/\sqrt{3}$ between phases b and c . In the case of unbalanced and distorted systems, this VCO uses a PI regulator and is based on a nominal $\omega_n = 2\pi f_n$. It outputs the estimation of θ_d is $\hat{\theta}_d$.

In our work, we are proposed to replace the PI regulator by a PI-neural regulator able to adapt to every changing parameters of the electrical network.

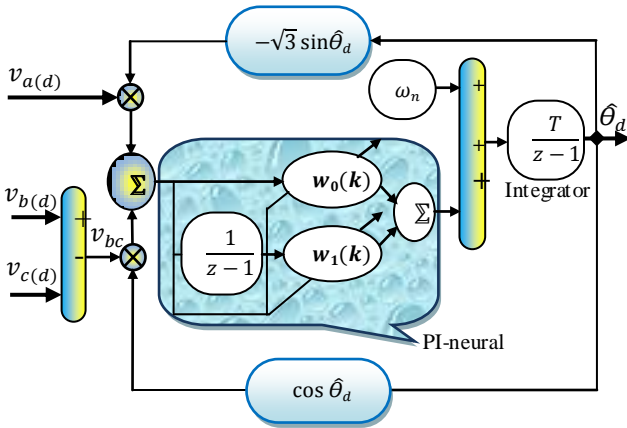


Fig. 6. Proposed (VCO) instantaneous phase detection based of The neural PI regulator.

This PI-neural employs an Adaline network to adjust the parameters proportional and integral. Complete functional block diagram of this VCO-neural is shown by Fig. 6 [12, 7, 13].

This PLL is not sensitive to the distortions in the voltage waveforms and is able to operate under unbalanced and distorted conditions.

5. Harmonic currents identification: the Neural Synchronous Method

Since the last decade, different ANNs identification and filtering techniques have been applied in power systems and Adaline networks are actually widely used [1].

In this paper, neural scheme for harmonic currents identification is developed and work in a current space. The method is based on synchronized currents and allows to clearly identifying the harmonic terms and thus to compensate for them with different objectives: full compensation, selective harmonic compensation, power factor correction, unbalance correction, and power flow control.

This approach is valid under balanced conditions. In the case of unbalanced nonlinear loads or

unbalanced voltage system, a symmetrical component extraction algorithm is necessary in order to estimate the Instantaneous phase (frequency) and the direct voltage components and, this can be achieved by our PLL-neural proposed in this paper and schematized by the fig.4.

5.1. Principle

The Neural Synchronous Method relies on the idea of synchronizing the identified fundamental current with the direct voltage component of the power system in order to maintain a unit power factor. A neural network is used to learn the load current decomposition and allows to extract the frequency and the phase-shift angle from the fundamental current. The references currents are then deduced and synchronized with the main source voltage through a PLL extracting the phase and the frequency of the positive voltage component. These reference currents represent the input for the control loop of an inverter and are therefore injected phase-opposite in the power system [10]. The principle of this method is described by Fig. 7.

The current synchronization is achieved by a PLL. In this paper, Our PLL-neural proposed (fig.4) is used instead of the conventional PLL under unbalanced conditions.

The objective of the compensation is to recover sinusoidal current waveforms which are in phase with the direct voltage components. As a consequence, the total free and available power transmitted from the source to the load will be at its maximum.

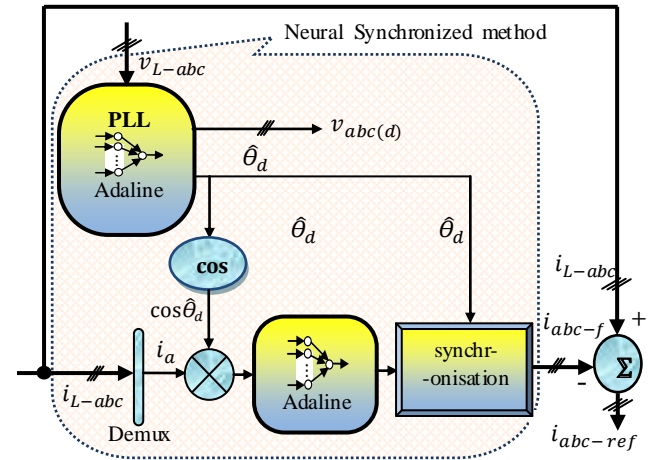


Fig.7. Principle of the neural Synchronous method.

The three-phase current with only the direct components can be written by [12]:

$$\begin{bmatrix} i_{L1} \\ i_{L2} \\ i_{L3} \end{bmatrix} = I_1 \begin{bmatrix} \cos(\theta_d + \varphi_1) \\ \cos(\theta_d + \varphi_1 - 2\pi/3) \\ \cos(\theta_d + \varphi_1 + 2\pi/3) \end{bmatrix} + \sum_{n=2}^N I_n \begin{bmatrix} \cos(n\theta_d + \varphi_n) \\ \cos(n\theta_d + \varphi_n - 2\pi/3) \\ \cos(n\theta_d + \varphi_n + 2\pi/3) \end{bmatrix} \quad (15)$$

Where φ_n is the phase of harmonic term of rank n

expressed between the voltage and the current components. On the other hand, the first element represents the currents issued from the fundamental frequency and the second element the currents issued from all the other harmonics.

Multiplying the measured load current of the first phase with only one term, either $\sin \theta_d$ or $\cos \theta_d$ issued from the symmetrical components extraction algorithm gives, if we show $\cos \theta_d$:

$$\begin{aligned} i_{L-a} \cos \theta_d &= \sum_{n=1}^N \frac{I_n}{2} [\cos((n+1)\theta_d + \varphi_n) \\ &\quad + \cos((n-1)\theta_d + \varphi_n)] \\ &= \sum_{n=1}^N \frac{I_n}{2} [\cos(n+1)\theta_d \cdot \cos \varphi_n - \sin(n \\ &\quad + 1)\theta_d \cdot \sin \varphi_n] \\ &\quad + \sum_{n=1}^N \frac{I_n}{2} [\cos(n-1)\theta_d \cdot \cos \varphi_n - \sin(n \\ &\quad - 1)\theta_d \cdot \sin \varphi_n] \end{aligned} \quad (16)$$

5.2 Adaline neural networks to identify harmonics distortions

The Neural Synchronous Method uses one Adaline instead of the low-pass filter utilized in the previous developments. Fig. 8 describes the Adaline structure with the input vector being the AC components developed in (16). This expression (16) is a weighted sum of harmonic terms which can be decomposed with the following generic vectors:

$$W^T = \begin{bmatrix} \frac{I_1}{2} \cos \varphi_1 & -\frac{I_1}{2} \sin \varphi_1 & \dots & \frac{I_n}{2} \cos \varphi_N \\ \frac{I_n}{2} \sin \varphi_N \end{bmatrix} \quad (17)$$

$$X(t) = \begin{bmatrix} 1 + \cos 2\theta_d t \\ \sin 2\theta_d \\ \vdots \\ \cos(N-1)\theta_d + \cos(N+1)\theta_d \\ \sin(N-1)\theta_d + \sin(N+1)\theta_d \end{bmatrix} \quad (18)$$

The fundamental current is thus obtained by multiplying i_{L-a} by $\cos \theta_d$ with $N = 1$:

$$\begin{aligned} i_{L-a} \cdot \cos \theta_d &= \frac{I_1}{2} [\cos \varphi_1 + \cos(2\theta_d + \varphi_1)] \\ &= \frac{I_1}{2} [\cos \varphi_1 (1 + \cos 2\theta_d) - \sin \varphi_1 \sin 2\theta_d] \end{aligned} \quad (19)$$

Expression (16) is learned with one Adaline using $X(t)$ as an input $i_{L-a} \cdot \cos \theta_d$ its desired output. θ_d is estimated by symmetrical components extraction algorithm. The learning therefore enforces the weights vector to converge toward W . The values of the two first weights (the DC components):

$$w_0 = \frac{I_1}{2} \cos \varphi_1 \quad \text{and} \quad w_1 = -\frac{I_1}{2} \sin \varphi_1 \quad \text{are thus}$$

associated to the direct fundamental sinusoidal term of the load currents and can be used to calculate I_1 and φ_1 :

$$I_1 = 2 \sqrt{w_0^2 + w_1^2} \quad (20)$$

$$\varphi_1 = \arctan \frac{-w_1}{w_0}$$

In the same way, it is possible to calculate the amplitude and phase of each harmonic term, I_n and φ_n , by using the corresponding Adaline weights harmonic term can thus $w_{n-1} = \frac{I_n}{2} \cos \varphi_n$ and $w_n = -\frac{I_n}{2} \sin \varphi_n$. Each be taken into account individually.

As shown by Fig. 8, the fundamental current i_{Lf} is extracted from the Adaline's weights. This current is then synchronized with the source voltage v_{s-abc} through the PLL. The synchronized reference current is obtained with $i_{ref-a} = i_{L-a} - I_{Lf} \text{sync}$.

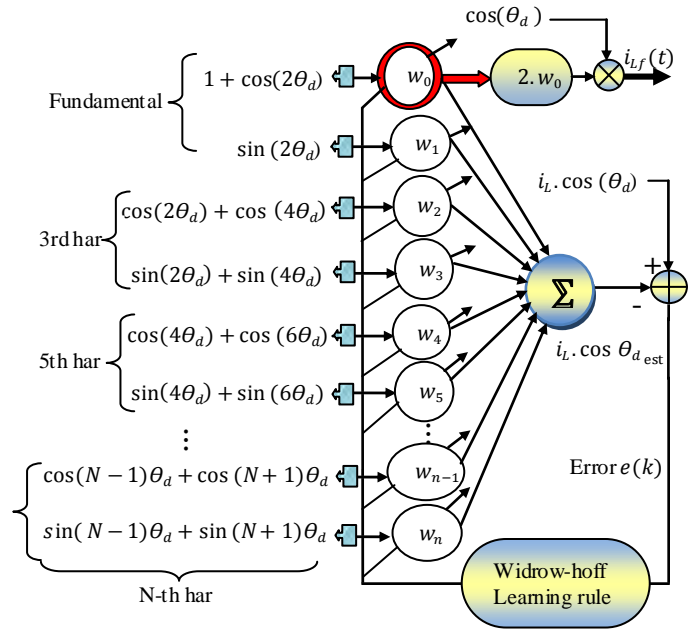


Fig. 8. Adaline for harmonics identification with the synchronous method.

In fact, the reference current for compensating for of all harmonics at once can be calculated by the sum of the higher-order harmonics or more simply by:

$$i_{ref-a} = i_{L-a} - I_1 \cos \varphi_1 \cos \theta_d \quad (22)$$

With $I_1 \cos \varphi_1 \cos \theta_d$ is an active current in phase with the direct voltage component and represents the active fundamental term of the load current. As a consequence, a compensation scheme with reference currents provided by (22) inherently maintains the power factor to unity.

6. Neuro-control of the inverter

After having identified the distortion harmonics,

the resulting reference currents have to be injected phase-opposite in the electrical power systems. This is generally done with an inverter and a supply filter implemented by analog circuits. Different algorithm strategies can be applied to control the inverter and inject suitable signals in regard to reference signals estimated previously. Hysteresis band controller, PID controller, and also RST controller are widely used in recent literature [3].

The control block of an inverter can be devised into two under blocks: the first one known as rapid which is related to the currents, and another known as slow which is associated to the DC-link voltage. So, one can synthesize two controllers, one for the internal loop of the currents and another for the external loop of the DC-link voltage.

6.1. PI-Neural control of inverter

For a few years, ANN techniques have been applied with success in control of APF and are very promising in the field. Indeed, the learning capabilities of the ANNs allow an online adaptation to every changing parameter of the electrical network, e.g., nonlinear and time-varying loads [9]. In this paper, we propose to determine the proportional and integrator parameters (respectively P and I) with the learning capabilities of neural networks. The principle is detailed by Fig. 9 where an Adaline neural network with two weights is used, the first one $w_0(k)$ as the proportional parameter (P), and the second one $w_1(k)$ as the integral parameter (I). These weights relate the errors e_k and e_{k-1} to the output $u(k)$ in a linear combination. This error is defined between the reference signal delivered to the regulator and the output of the system to be controlled. This error is used to update the weights of the Adaline and is at a given sample time $e_k = i_{ref}(k) - i_{inj}(k)$.

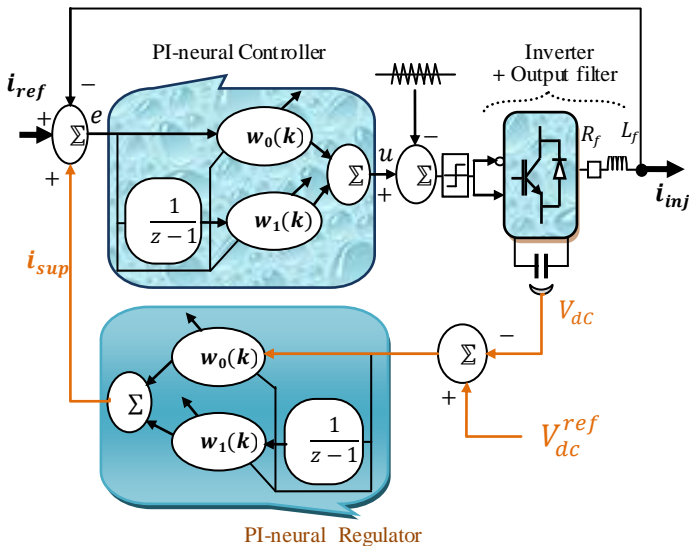


Fig.9. The neural PI regulator scheme applied to the control of an inverter.

In this neural architecture, the PI parameters are adapted and learned on-line to converge toward optimal values. The neural PI controller, enhanced with this learning process is able to handle every changing parameters [8].

6.2. DC voltage control

In this work, To compensate the inverter losses and maintain the DC-link voltage V_{dc} constant, a neural proportional integral controller (PI-neural) is used to obtain the compensation current i_{sup} . The control loop compares the measured voltage V_{dc} with the reference voltage V_{dc}^{ref} and generates corresponding current i_{sup} .

7. Computer Simulation results

In order to test the performance and the robustness of the proposed neural active filter (APF-neural) based on a complete neural strategy for the harmonic distortions compensation under industrial operating conditions, i.e. unbalanced load and unbalanced voltage supply, the system of Fig.2, was simulated in MATLAB-SIMULINK. Simulation parameters used in this paper are summarized in Table 1.

Table 1. Parameters of Simulation

The three-phase supply	balanced	$V_s = 240\sqrt{2} \text{ V}$
	Unbalanced	$V_{sa} = 240\sqrt{2} \text{ V}$
		$V_{sb} = 220\sqrt{2} \text{ V}$
		$V_{sc} = 200\sqrt{2} \text{ V}$
	Frequency	$f = 50 \text{ Hz}$
Resistances	$R_s = 3.5 \text{ m}\Omega$ $L_s = 0.05 \text{ mH}$	
Nonlinear load	A Graetz bridge with RL branches and six function with an angle $\alpha=0^\circ$ $R_L = 1 \Omega$, $L_L = 2.6 \text{ mH}$	
Lines characteristics	$R_c = 0.82 \text{ m}\Omega$, $L_c = 0.023 \text{ mH}$	
Output filter	$R_f = 5 \text{ m}\Omega$, $L_f = 50\mu\text{H}$	
Capacitor (regulation)	$V_{dc} = 840 \text{ V}$, $C = 8\mu\text{F}$	
Sampling period	$T_s = 1 \mu\text{s}$	

7.1. Harmonics detection block

The APF-neural inserted in the power system described above in order to compensate for the harmonic distortions induced by the nonlinear load which is an unbalanced system. The previous neural approach called the neural synchronous method (fig.7) is used to identify the harmonics and to compute the APF's reference currents. This neural approach uses one Adaline per phase. By considering the fundamental current and the harmonics of row 3, 5, 7, 11, These Adalines will have 10 inputs. During the training, the choice of the constant learning is $\mu = 0.0001$. The neural

synchronous method is sensitive to the frequency fluctuations, thus with an unbalanced distorted supply voltage, our harmonics identification schemes need the direct voltage components and the instantaneous phase, As a consequence, the insertion of PLL scheme is necessary.

7.2. Performance of the proposed PLL-neural

In this paper, the proposed PLL-neural is also based on the IPT with a PI-neural regulator have been implemented in order to estimate instantaneously the direct voltage components and the frequency (fig.4). The direct and inverse voltage components extractor is evaluated by simulations. With a constant learning rate $\mu = 0.0001$, we used two Adalines with 16 inputs for find the direct voltage components, and two others for extracted the inverse voltage components (Fig.5). The robustness of our approach is now valuated for estimating the voltage components in a simulated

electrical network with time varying parameters. At starting, our PLL is tested with voltages polluted by the 3rd and 5th harmonics (Fig.11) and then with unbalanced voltage (Fig.12). Compared with the conventional PLL the direct voltage components estimated by the two methods, the conventional PLL and the PLL-neural with 2 Adalines (based on the IPT), are depicted by Fig. 11.b, c, e, and Fig.12.b, c, e.

By visualizing table 2, After compensation, with the APF-neural controlled by a PI-neural, the THD is significantly reduced from 25.04% to 1.99% using the conventional PLL, to 0.30% using the PLL-neural proposed and the power factor PF is increased from 0.7067 to 0.9992. Indeed we can clearly see that the PLL-neural is faster than the conventional PLL. Our proposed PLL-neural based on the IPT with a PI-neural controller, serves as a reference in term of performance.

Table. 2. Comparison between the PLL conventional / PLL neural and hysteresis controller / PI-neural controller

Unbalanced voltage Supply		With compensation (the Neural Synchronous method)				Without compensation (APF)
		PLL conventional		PLL neural (based on IPT)		
		Hyst. Controller	PI-neural Controller	Hyst. Controller	PI-neural Controller	
THD (%)	Balanced Nonlinear- load	1.73	1.99	0.24	0.30	25.04
	Unbalanced nonlinear-load	1.83	1.99	0.27	0.30	
Power factor	Balanced Nonlinear- load	0.7068	0.7066	0.999	0.9989	0.9596
	Unbalanced nonlinear-load	0.7069	0.7067	0.9992	0.9992	
PF		0.7093	0.713	0.9898	0.9898	

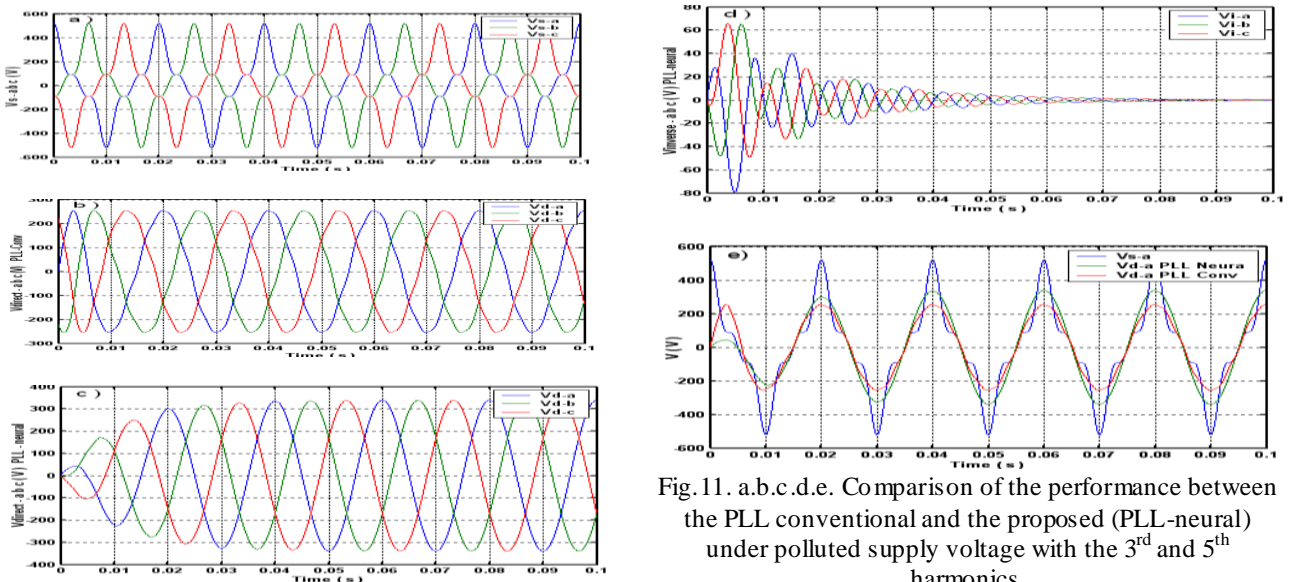


Fig. 11. a.b.c.d.e. Comparison of the performance between the PLL conventional and the proposed (PLL-neural) under polluted supply voltage with the 3rd and 5th harmonics.

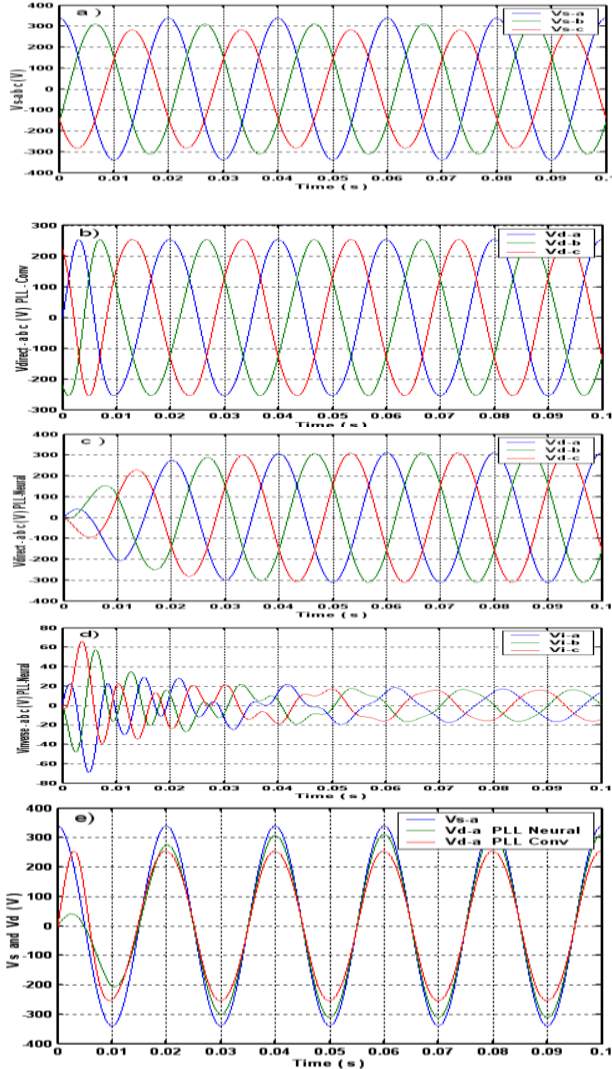


Fig. 12. a.b.c.d.e. Comparison of the performance between the PLL conventional and the proposed (PLL-neural), under unbalanced supply voltage.

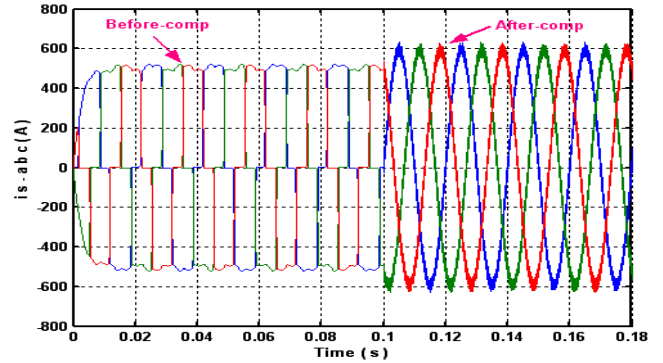
8. Comparative results

The efficiency and the robustness of the proposed neural active power filter (APF-neural) using the neural synchronous method associated to a PI-neural control scheme is demonstrated with simulation.

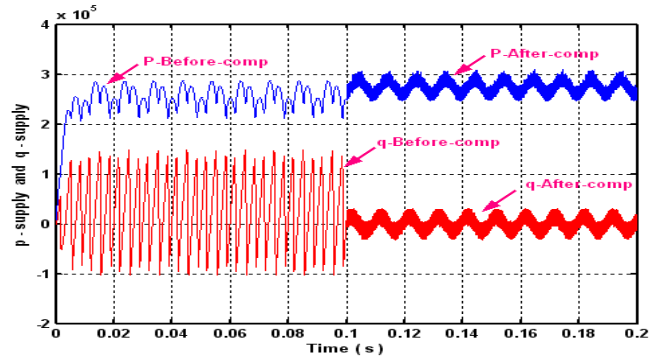
8.1 Results without and with compensation

Under balanced load, the insertion of our proposed APF-neural is done after $t = 0.1$ s so, we can easily compare the results without and with compensation (Fig.13). As illustrated in Figure 13.b shows the variation of active and reactive power before and after filtering without and with APF-neural. It can be seen that the active power is relatively constant, but the reactive power is approximately equal to zero after compensation. The results clearly illustrate the successful and effectiveness elimination of reactive power. From Fig.13.d we can see as well that the current source after active filter application is approximately sinusoidal and in phase with the voltage source. As

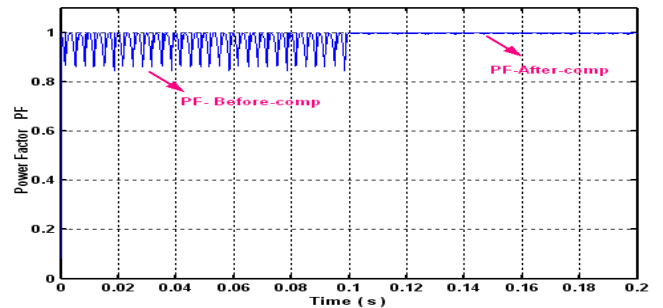
consequence, the power factor PF converges to the unity (Fig.13.c). Fig.13.a, shows simulation results for three-phase three-wire system, where the nonlinear load draws distorted currents from the source (it is highly distorted and rich on harmonics), After APF injects compensating currents then source currents become nearly sinusoidal with low THD.



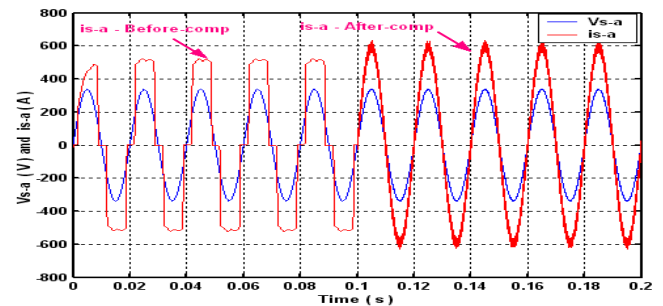
a. Evolution of three-phase line currents.



b. Evolution of the instantaneous powers supply.



c. Evolution of the power factor.



d. Evolution of supply voltage and currents (phase-a).

Fig. 13.a.b.c.d. Response of the neural APF without and with compensation, under balanced load, when the APF is inserted at time $t=0.1$ s.

8.2 Effect of the online varying load (unbalanced load)

We proposed a simulation with an on-line varying load, i.e., a sudden change of the linear load in order to evaluate the dynamic responses and test the robustness of the proposed techniques (APF-neural). The amplitude of the harmonic components are modulate by changing of value of R_L from $R_L/2$ à l'instant $t = 0.1$ s.

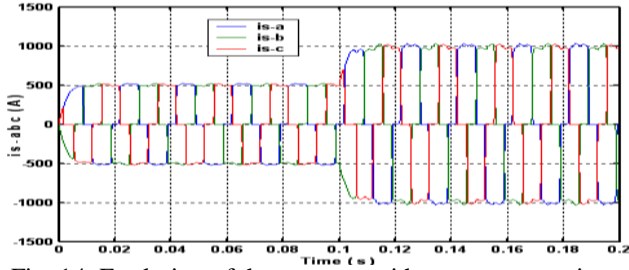


Fig. 14. Evolution of the currents without compensation when the nonlinear load is simulated and changed at time $t=0.1$ s.

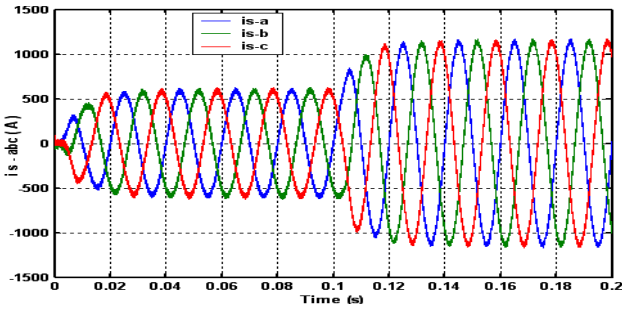


Fig. 15. Evolution of three-phase currents with compensation when the nonlinear load is simulated and changed at time $t=0.1$ s.

The proposed Adaline strategy succeeded in detecting the transients and in identifying the effects resulting from the nonlinear load changes. Also as can be seen from Fig. 15, the line current takes a form very close to a sinusoidal and from Figure 16.d, the injected currents harmonic into the line by the active filter modules follow their references. The waveforms clearly illustrate the successful elimination of the selected harmonics from the line current. From Fig. 16.a we can see the phase shift between current and voltage source, this phase shift make a degradation of power factor that we want to make very closer to unity (Fig. 16.e).

The Fig.16.c shows the transients of the reference current of one phase and of the current injected into this phase by using the neural PI approach. As can be seen, the PI- neural regulator is efficient. Indeed, the current estimation error, called the static current error (Fig. 16.d), has converged to 9.36 % after 40 ms (response time of the PI-neural regulator). Also, the Figure17 shows the performance of this PI-neuro-control approach to stabilize the dc voltage to its reference $V_{dc}^{ref} = 840$ V.

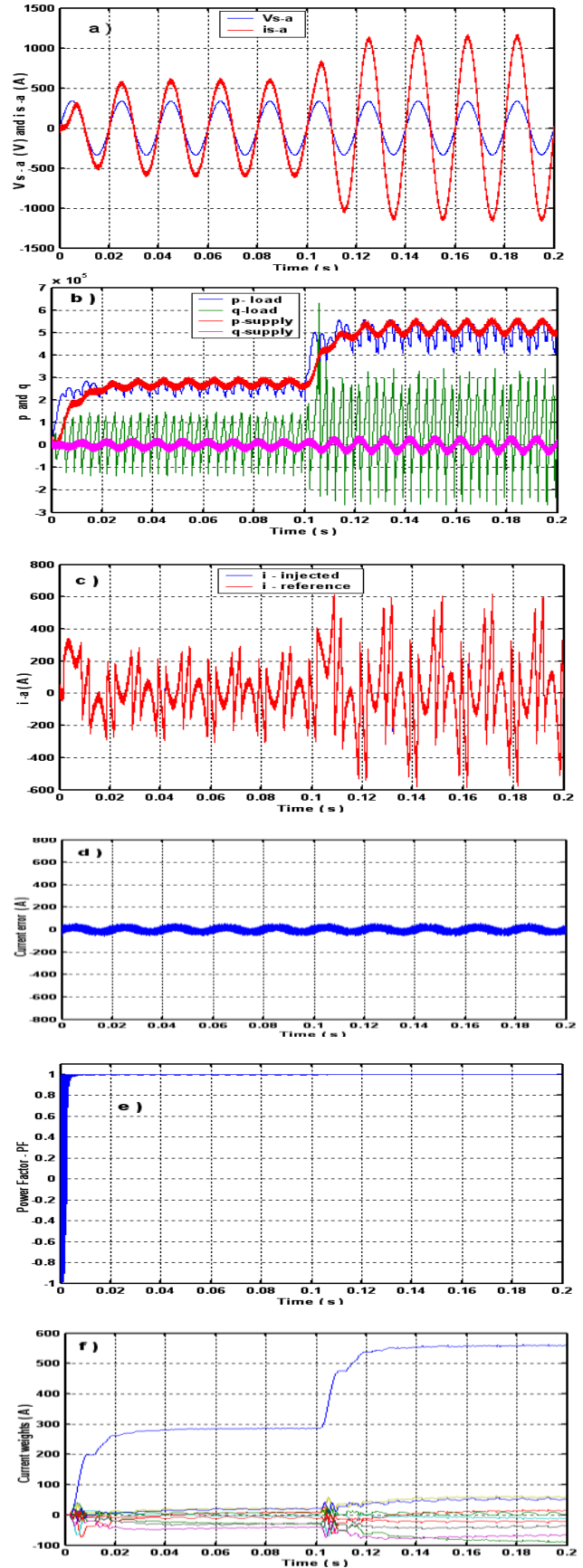


Fig. 16.a.b.c.d.e.f. Dynamic response of the neural APF when the nonlinear load is simulated and changed at time $t=0.1$ s.

8.3. Results under unbalanced / polluted supply voltage

Under unbalanced supply voltage, Fig.18 show the harmonic spectrum of the waveforms distorted (phase-a) current with a Total Harmonic Distortion rate equal to 25.04% before filtering. After filtering with the neural synchronous method, this THD is decreased to a value of 0.30% (Fig.19) and the power factor PF is 0.9992 (Tab.2).

On the other hand, under polluted supply voltage with the 3rd and 5th harmonics, the waveforms of the current (phase-a) and its harmonic spectrum is showed by Fig.20.a and Fig.20.b. That the THD equal to 0.95% (before filtering), and the power factor is 0.9898 (Tab.2).

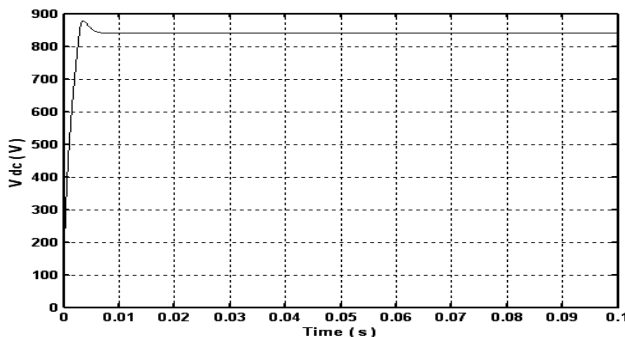


Fig. 17. DC voltage capacitor using PI-neural controller.

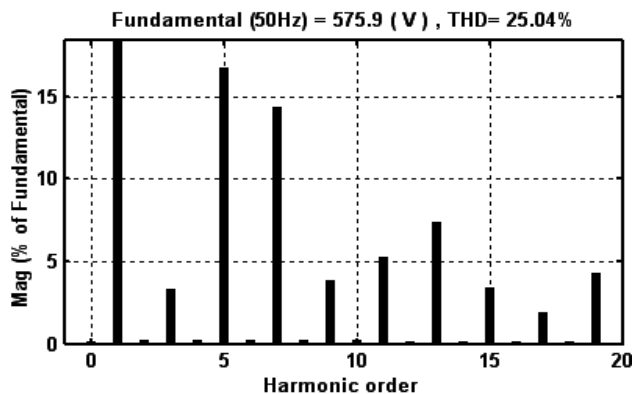


Fig. 18. The Harmonic Spectrum of the Distorted Current of the phase-a before compensation.

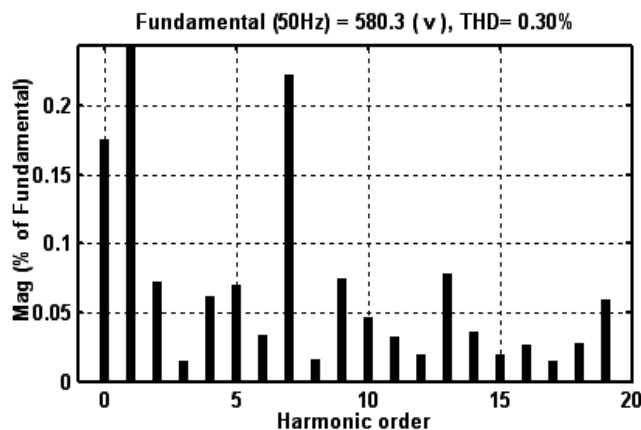


Fig. 19. The Harmonic Spectrum of the Current of the phase-a after compensation: under unbalanced supply voltage.

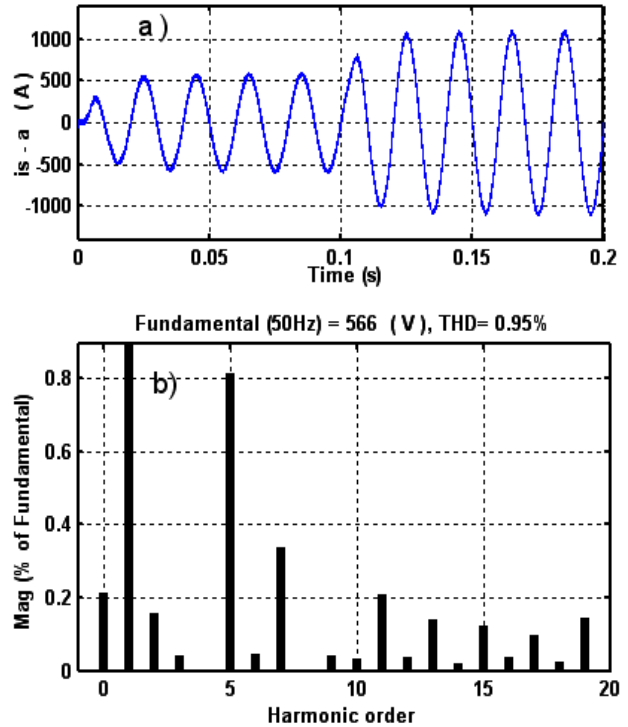


Fig. 20. a. Current of the phase-a. b. Its Harmonic Spectrum after compensation: under polluted supply voltage with the 3rd and 5th harmonics.

8.4. Discussion

Static and dynamics tests show that the performance of our APF-neural is quantified through Tab.2 which gives the THD and the PF resulting from different Consideration. i.e., PLL- conventional /PLL-neural, hysteresis controller/PI-neural controller, under unbalanced/polluted supply voltage and balanced/unbalanced nonlinear load. As consequence, all the results show that the neural approach is very fast, efficient and robust.

9. Conclusion

In this paper, we are succeed to build an intelligent active power filter (APF) control unit for harmonics current elimination , reactive power compensation (power factor correction) and selective harmonic compensation. This filter is completely based only of Adaptive Neural Networks (Adalines), indeed, our main motivation remains of tending toward a “complete neuromimetic” strategy was achieved. that the Adalines are involved in identification of harmonic currents, as well as in the control scheme of the inverter, in the regulation of the dc voltage and in the one-line extraction of the direct and inverse voltage components (PLL). The Simulation results obtained on transient and steady states show the effectiveness of the proposed shunt APF-neural in different operation conditions. It is able to compensate for the disturbances even while the nonlinear load changes and even while the system is unbalanced and it is able to adapt itself in real-time to any changes of the power supply network parameters. After compensation the source

current is balanced, sinusoidal and in phase with line voltage source. The harmonic spectrum shows that the THD using PI-neural controller is very acceptable and respect IEEE standard Norms (THD ≤ 5). As consequences, this proposed neural compensation technique (APF-neural) is better than the conventional APF for the determination and for the reduction of the harmonic distortions. Moreover, results show excellent behaviors and performances, as well as robustness and usefulness.

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