

A NEW ACTIVE POWER LINE CONDITIONER FOR COMPENSATION IN UNBALANCED/DISTORTED ELECTRICAL POWER SYSTEMS

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Abstract – A new control design of an Active Power Line Conditioner (APLC) for unbalanced/distorted electrical power system compensation is presented. The APLC is built by an dc-ac power converter and a control circuit. In this paper, the control circuit is a new design based in two types of artificial neural networks (ANNs). An adaptive linear neuron (ADALINE) estimates the reference compensation current and a multilayer feedforward network carries out a pulse width modulation (PWM) control. The resultant compensation system eliminates harmonics, reactive power and unbalanced currents with a quick dynamic response. Last, two digital simulations to check the proposed control performance are presented.

Keywords: *Power Quality, Harmonics, Power factor correction, Active power filters, Adaptive control, Neural network*

1 INTRODUCTION

In the last years, the indiscriminate use of non-linear loads have supposed an increase of voltage and current waveform distortion in electrical power systems. On the other hand, the utilization of larger single-phase consumers imply serious unbalance problems in three-phase systems. Thus, in general, three-phase electrical power systems need a set of equipments to correct the asymmetry and the distortion that systematically pollute the electric power quality.

The APLC is a method, between other ones, based on power electronic that permits to correct the electric power quality deficiencies, [1-3]. The APLC is a compensation system built by two basic circuits: a dc-ac power converter and a control circuit. Nowadays, the power converter of major utilization is the named voltage-source inverter based in a bridge configuration with six IGBTs, fig. 1. Two capacitors are connected in the dc side with a common dc busbar, that ensures the presence of the neutral wire with a reduced number of electronic devices, [3].

The control circuit is built by the reference current generator and the PWM control, mainly, the ramp comparator or the hysteresis band comparator. The ramp comparator method compares the error between actual and reference compensation currents to a triangular

waveform to generate the inverter firing pulses. The advantage is that the inverter switching is limited to the frequency of the triangular waveform; however, there are phase and amplitude errors. In the hysteresis band controller method, the currents will stay in a band around the reference currents; this scheme provides excellent dynamic performance but is not possible to know the switching frequency. In short, the suitable sequence of IGBTs firing signals allows to synthesize a compensation current that follows the reference waveform.

The major research works of the last twenty years are related with control circuit designs. The target is to obtain reliability control algorithms of the reference current and a quick response procedure to get the control signal. The Artificial Neural Networks (ANNs) have been systematically applied to electrical engineering, [4-6]. Nowadays, this technique is considered as a new tool to design APF control circuits. The ANNs present two principal characteristics. It's not necessary to establish specific input-output relationships but they are formulated through a learning process or through an adaptive algorithm. Moreover, the parallel computing architecture increases the system speed and reliability, [7-10].

In this paper, a new APF control method based on Neural Networks will be presented. Load voltages and currents are sensed, the control block calculates the power circuit control signals from the reference compensation currents, and the power circuit injects the compensation current to the power system.

Next items describe the topology of the Artificial Neural Networks (ANNs) used in the APF control. In section 2, a new method to control an active power filter with ANNs is presented, and sections 3 and 4 will complete the description of ANNs blocks included. In section 5, it will be shown how the electrical system and its compensation can be simulated in Matlab-Simulink application. The results of two practical case will be presented, the compensation by shunt APF of a three-phase unbalanced ac regulator and the compensation of a controlled three-phase converter.

2 PRINCIPLES OF AN ACTIVE POWER FILTER WITH NEURAL NETWORKS

A system with a non-linear three-phase load with voltage supply is considered. A shunt Active Power Filter is used to generate the compensation current. The non-linear load current i_L is the sum of the source current i_S and the compensation current i_C . The target is to get a balanced supply current without harmonic and reactive components. The suitable compensation current injected by the shunt APF corresponds to the load current non-active component. The APF power circuit proposed is a three-phase IGBTs bridge inverter with a split capacitor in dc side, to compensate three-phase, four-wires, unbalanced non-linear loads, [3], figure 1.

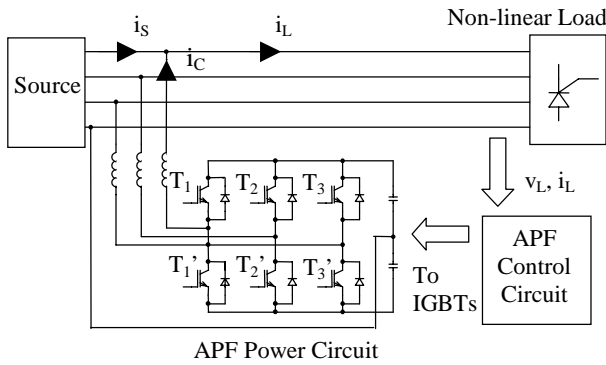


Figure 1: A three-phase four-wire system with shunt Active Power Filter.

In this paper, a shunt APF with a new hysteresis band control is used to compensate the non-linear loads. The target is to control the compensation currents to follow the reference ones. The switching strategies of the three-phase inverter will keep the currents into the hysteresis band.

The control block generates the IGBTs trigger signals. A basic scheme of hysteresis band control is shown in figure 2. Here, a feedforward ANN is proposed to work as the habitual non-linear relay.

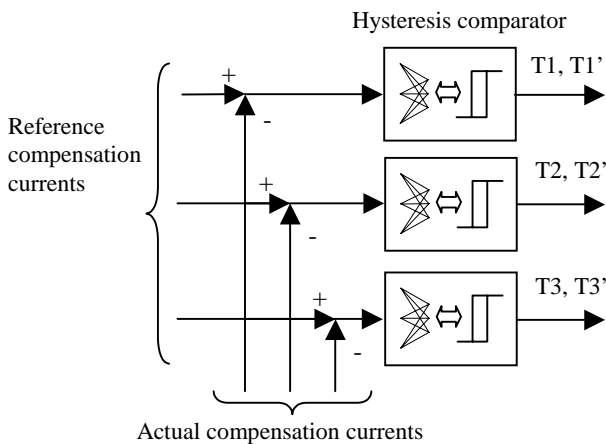


Figure 2: Diagram of ANN Hysteresis band control .

The actual load currents are sensed, their estimated non-active components are the reference compensation currents, which are compared with the actual compensation currents. The differences are the inputs of hysteresis comparator blocks, and their output signals are used to turn on/off the inverter switches. The compensation current will stay in a band around the reference signal.

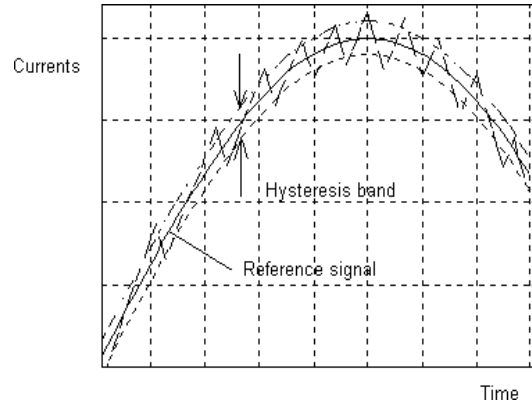


Figure 3: Control reference and actual currents.

The control is built by two blocks. The first one is developed with adaptive networks (Adaline neurons), which allow to make on-line estimation of control reference compensation currents. The second one is a feedforward network. After a training process, it works on-line as comparator between reference waveforms and actual compensation currents, figure 4.

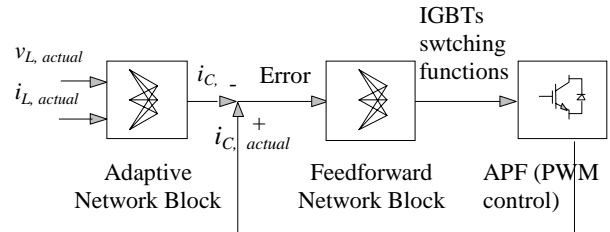


Figure 4: Block diagram of Active Power Filter control.

The inputs of the first block are load voltages ($v_{L,actual}$) and load currents ($i_{L,actual}$). This block estimates the compensation currents which are going to be used as reference in the control system, ($i_{C,ref}$). The inputs of the second block are the differences between actual and reference compensation currents, signals *Error* in figure 4. If the error value, positive or negative, is greater than the hysteresis band, the trigger signals change, and the compensation current will decrease or increase respectively, figure 3. The actual compensation currents are the result of controlling the switching logic of power circuit devices.

The proposed control allows an excellent filter dynamic response, and the compensation currents can be adapted quickly to any change of load current. The results of two practical cases will be presented in section 5.

3 COMPENSATION REFERENCE CURRENT

3.1 Adaptive neural network principles

A periodic waveform can be expanded by Fourier analysis as sum of cosine and sine frequency components. The following model of signal to be estimated is proposed:

$$f(t) = \sum_{n=1, \dots, N} [X_n \cos(n\omega t) + Y_n \sin(n\omega t)] \quad (1)$$

where X_n e Y_n are the amplitude of *cosine* and *sine* components of the order- n harmonic. In vectorial form:

$$f(t) = \mathbf{W}^T \cdot \mathbf{x}(t) \quad (2)$$

where:

$$\mathbf{W}^T = [X_1 Y_1 \dots X_N Y_N] \quad \text{and} \quad \mathbf{x}(t) = \begin{bmatrix} \cos \omega t \\ \sin \omega t \\ \dots \\ \cos N\omega t \\ \sin N\omega t \end{bmatrix} \quad (3)$$

The signals are sampled with uniform rate, Δt . So, the time values are discrete, $k \Delta t$ with $k=0,1,2,\dots$. The dot product presented in (2) is carried out by an Adaline network, where W is the network weights vector. After the initial estimation, an adaptive algorithm updates the weights. Thus, the estimated signal converges to the actual one. Figure 5 shows the network topology and the weights update algorithm. $x(k)$ is the cosine/sine vector and $f_{actual}(k)$ is the actual signal. The neurons, taking into account their weights $W(k)$, carry out an estimation $f_{est}(k)$. The error $e(k)$ is the difference between the actual signal and its estimation. An algorithm allows to get the weights to be used in the next iteration $W(k+1)$, which minimizes that error. After this iterative process the estimated signals adapt to the actual signals.

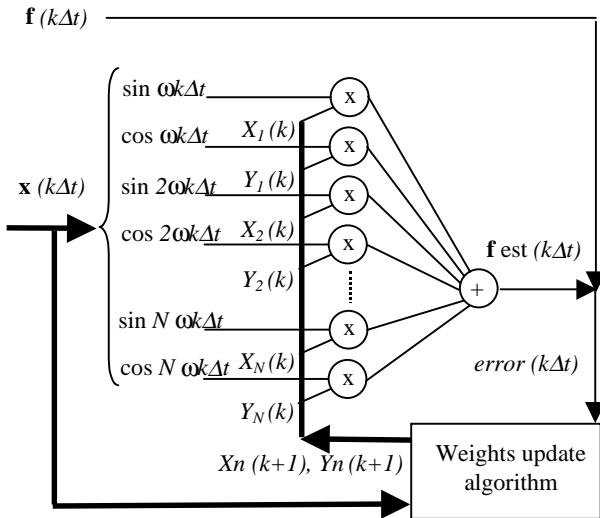


Figure 5: Adaptive network topology.

The weight adaptation algorithm is a modification of the Widrow-Hoff (W-H) algorithm, [7],[9-10], which minimize the average square error between actual and estimated signals. It can be written as follows:

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \frac{e(k) \mathbf{x}(k)}{\mathbf{x}^T(k) \mathbf{x}(k)} \quad (4)$$

Equation (4) is the W-H rule. The scalar product $\mathbf{x}^T(k) \mathbf{x}(k)$ is the norm of the vector $\mathbf{x}(k)$. So, in each iteration, weights are adjusted proportionally to the error and they follow the $\mathbf{x}(k)$ unitary direction. A modification of W-H rule can be written as follows:

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \frac{\alpha e(k) \mathbf{y}(k)}{\mathbf{x}^T(k) \mathbf{y}(k)} \quad (5)$$

In (5), $y(k)$ is the sign of $x(k)$, i.e., $y(k) = \text{sgn}(x(k))$. As $x(k)$ are sinusoidal signals, if signals sign is considered, the learning rate for the weight correction will increase. The convergence-settling time decreases, though the convergence is less stable. The authors have considered an average between the signal and the signal sign, [10]. Thus, it reduces the convergence problems.

$$y(k) = 0.5 \cdot \text{sgn}(x(k)) + 0.5 \cdot x(k) \quad (6)$$

Moreover, a learning parameter α is introduced to get a more stable convergence. The α parameter is modified as shown in the following equation.

$$\alpha = \alpha_0 + c_1 e + c_2 \dot{e} \quad (7)$$

Thus, α parameter, which depends on the linear error and its derivative, improves the algorithm convergence.

Both corrections influence the convergence in opposite way; this commitment must be achieved to get stable and fast enough convergence. The initial evolution of estimated signals depends on the initial weight choice. The evolution from another change doesn't depend on that initial choice.

3.2 Estimation of Voltage and Current Waveforms

As non-linear loads are present in the power system, load voltages and load currents can be expressed as shown in equations (8) and (9):

$$v_L = \sum_{n=1, \dots, N} [V_{n1} \cos(n\omega t) + V_{n2} \sin(n\omega t)] \quad (8)$$

$$i_L = \sum_{n=1, \dots, N} [I_{n1} \cos(n\omega t) + I_{n2} \sin(n\omega t)] \quad (9)$$

where ω is the fundamental pulsation, V_{n1} and V_{n2} are cosine and sin coefficients of harmonic components of

the load voltage and I_{n1} and I_{n2} are cosine and sin coefficients of harmonic components of the load current.

Two Adaline neurons estimate, per phase, the fundamental components of load voltage and current. Each active current is estimated from those fundamental components. With fundamental frequency coefficients of v_L and i_L estimated per phase, the load active current can be calculated without computing any integration. In fact, the target source active current per phase, i.e. L1, is:

$$i_{act,L1} = \frac{P}{V^2} v_{L1,1} = \frac{\frac{1}{T} \sum_{i=L1,L2,L3} \int_0^T v_{i,1} i_{i,1} dt}{\frac{1}{T} \sum_{i=L1,L2,L3} \int_0^T v_{i,1}^2 dt} v_{L1,1} \quad (10)$$

$$i_{act,L1} = \frac{\sum_{i=L1,L2,L3} \langle v_{i,1}, i_{i,1} \rangle}{\sum_{i=L1,L2,L3} \langle v_{i,1}, v_{i,1} \rangle} v_{L1,1} \quad (11)$$

The result of (11) is:

$$i_{act,L1} = \frac{\sum_{i=L1,L2,L3} V_{i,11} I_{i,11} + V_{i,12} I_{i,12}}{\sum_{i=L1,L2,L3} V_{i,11}^2 + V_{i,12}^2} (V_{L1,11} \cos(\omega t) + V_{L1,12} \sin(\omega t)) \quad (12)$$

The difference between actual load currents and their estimated fundamental active components are the non-active currents. They are used as reference compensation currents of the APF control circuit.

$$i_{comp,ref,L1} = i_{L1} - i_{act,L1} \quad (13)$$

The source currents of the compensated system become balanced and sinusoidal.

4 CONTROL OF COMPENSATION CURRENTS

In the previous sections, the method to obtain the control reference currents with Adaline networks was presented. In this section, the control circuit based on feedforward ANNs is developed.

4.1 Feedforward neural network principles

The Artificial Neural Networks (ANNs) consist of a large number of strongly connected elements. The artificial neurons represent a biological neuron abstraction carried out in a computer program. The artificial neuron model is shown in figure 6.

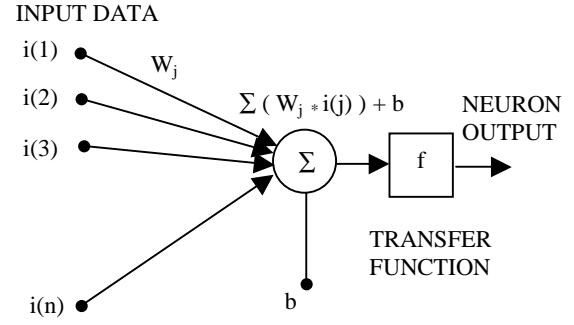


Figure 6: Artificial neuron model.

The input data $i(1)$, $i(2)$, $i(3)$, ..., $i(n)$ flow through the synapses weights and they are accumulated in the node represented as a circle. The weights amplify or attenuate the inputs signals before their addition. Once added, the data flow to the output through a transfer function f , that may be the threshold one, the sign one, the linear threshold one or the pure linear one. Otherwise, it may be a continuous non-linear function such as the sigmoid one, the inverse tangent one, the hyperbolic one or the gaussian one.

The neurons are connected conforming different layers. The most commonly adopted architecture is feedforward, as shown in figure 7.

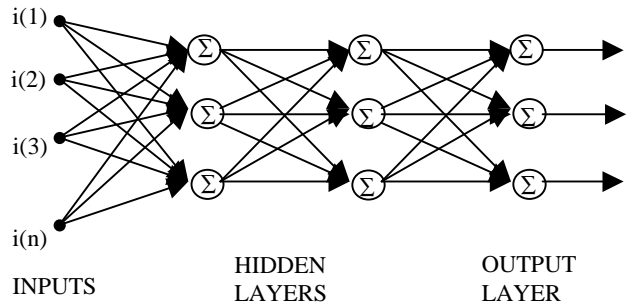


Figure 7: Feedforward Neural Network architecture.

The neural architecture consists of three layers: the input one, the hidden one and the output one. In the figure, the circles represent neurons. Thus, the feedforward architecture computes the input data in parallel way, faster than the computer sequential algorithms. This network can be trained to supply an output target when the corresponding inputs are applied. The most commonly used method is the backpropagation training algorithm. The initial weights are random. The initial output pattern is compared with the current output, and the weights are adjusted by the algorithm until the error becomes small enough. The training process is carried out by a program that uses a large number of input/target data, which can be obtained from simulations or experimental results.

4.2 Neural PWM Control

A feedforward Neural Network works as hysteresis comparator in the PWM control, figure 8. This network is designed with two inputs and two layers, the hidden with 14 neurons and the output layer with 1 neuron. The activation functions are log-sigmoid in the hidden layer and linear in the output layer. The training algorithm used is backpropagation.

The comparator outputs depend on the inputs and their evolution. The chosen configuration has two inputs, the error signal in t and its value in the previous time $t-1$. The network topology is shown in figure 8.

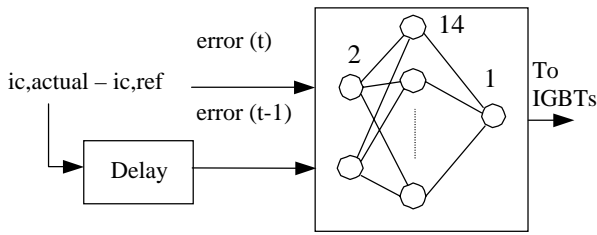


Figure 8: Topology of feedforward Network.

To fix the network weights, it's necessary to compare the network outputs with the outputs of a real electrical system.

5 RESULTS OF PRACTICAL CASES

5.1 Simulation Models

To check the proposed design, the electrical system, control block included, was simulated in Matlab-Simulink software.

A three-phase sinusoidal voltage supply, a non-linear load block and the power circuit of an active power filter were developed in the same software, computer-aided by the Power System Blockset, to get load voltages and currents of the electrical system. In figure 9, the Simulink diagram of the compensated electrical system is shown. The circuit will be simulated with two load block, a model of a three-phase converter and a model of a three-phase ac-regulator.

The control block is presented in figure 10. The adaptive network block estimates load voltages and currents. The difference between actual currents and their estimated active components are the non-active current used as compensation reference currents. On the other hand, the feedforward block works on-line as hysteresis comparator, its inputs are reference and actual compensation currents, and its outputs are the trigger signals of the power circuit IGBTs.

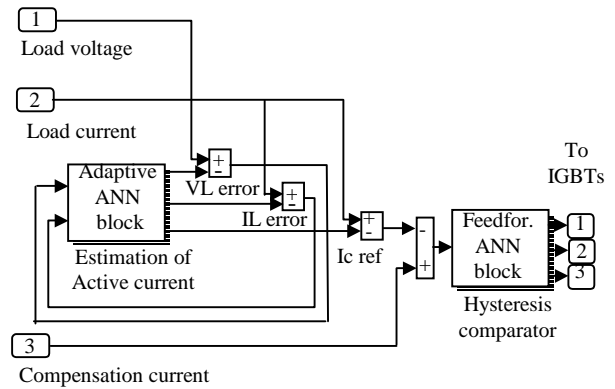


Figure 10: Simulink control block.

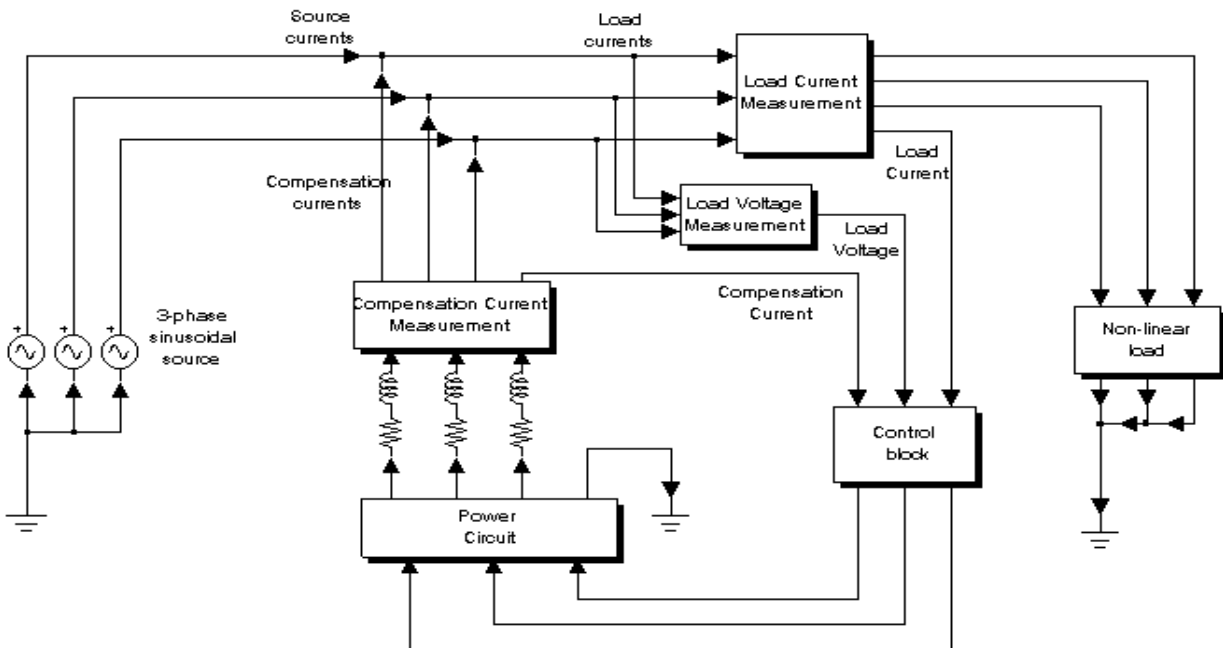


Figure 9: Simulink diagram of electrical system.

To train the feedforward network, it's necessary to know real system input and output signals. So, the electrical system was simulated in Simulink using a relay block as comparator to obtain inputs and target-output signals. To train the feedforward network, the Matlab Neural Networks toolbox was used. A training program using matlab routines was developed. *Initff* initialises Network weights, *Trainlm* carries out the training process to fix the final weights using pattern signals. After the training process, *Simuff* allows the network to work on-line as comparator. The error of this comparator block was specified at 0,1 % as maximum goal. The error signal during the training process is shown in figure 11.

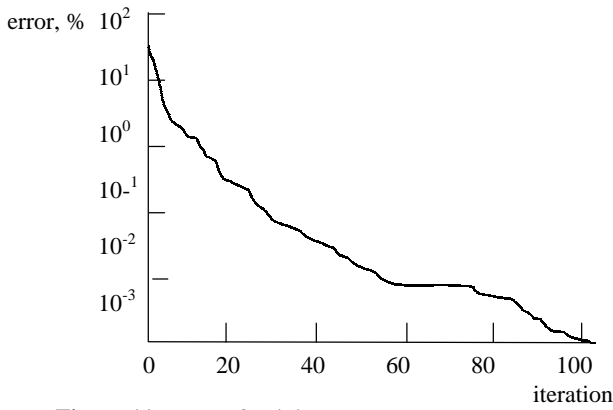


Figure 11: Error of training process.

5.2 Main results

Case 1. The proposed design was applied in a electric system with a three-phase balanced and sinusoidal voltage supply and a controlled three-phase rectifier. Next, it's shown the evolution of several waveforms per phase when the load is experienced a 50% change. Figure 12a presents load voltage. Actual and estimated load current are shown in figures 12b and 12c.

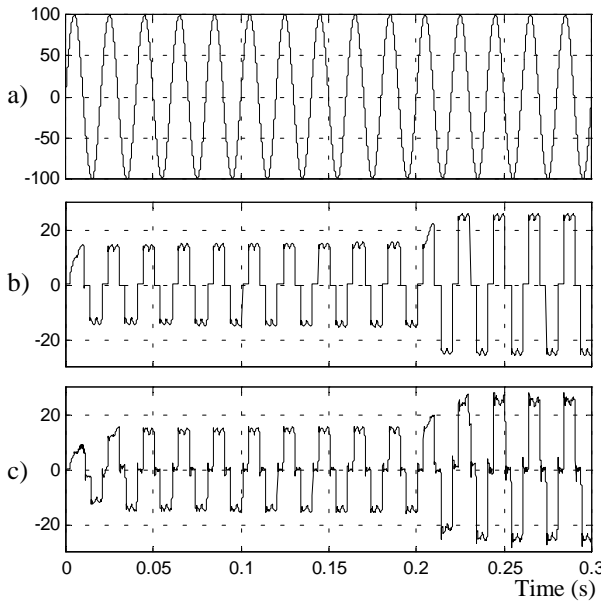


Figure 12: Case 1: Controlled three-phase converter. a) Load voltage; b) Load current; c) Estimated load current

The estimation of equivalent conductance, figure 13a, shows the transient process evolution. The compensation current, figure 13b, is the result of hysteresis band control used. Figure 13c presents the source current of the compensated system. The signal evolution depends on the initial weights of the adaptive networks. Those weights have been chosen null in this example. The dynamic response of power filter is one and a half period approximately.

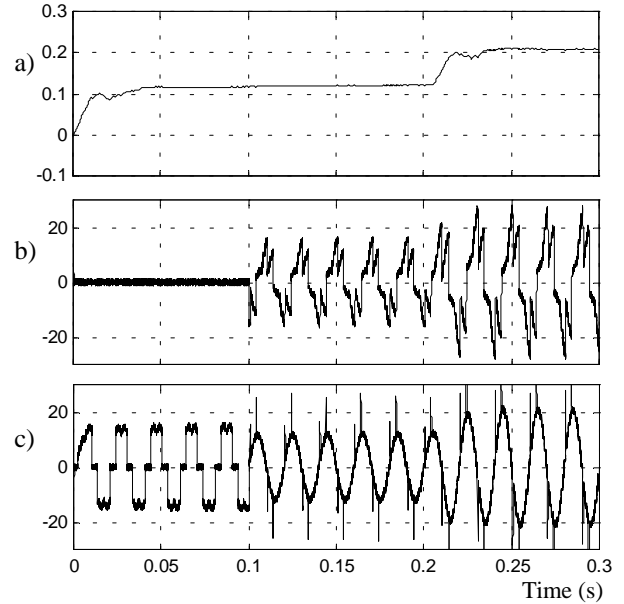


Figure 13: Case 1: Controlled three-phase converter. a) Estimated equivalent conductance; b) Compensation current; c) Source current

Case 2. On the other hand, a second practical case was simulated, an unbalanced three-phase ac-regulator. As above, figures 14 and 15 show the main results of this case. Besides, the neutral current is null in the compensated system, figure 15d.

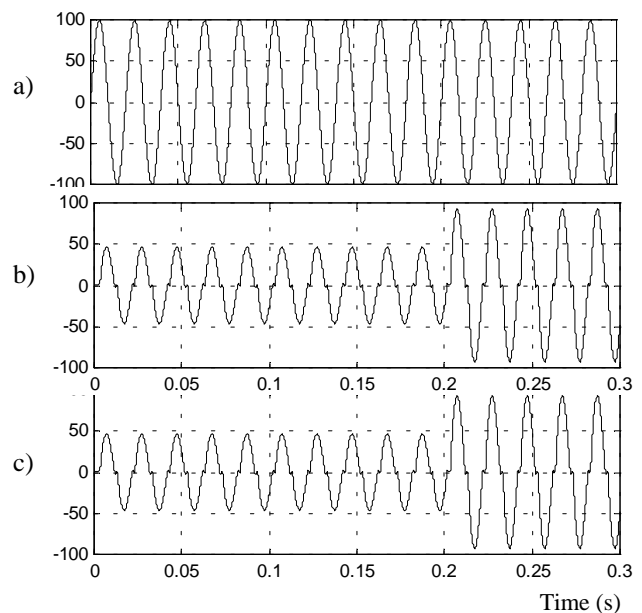


Figure 14: Case 2: Three-phase ac-regulator. a) Load voltage; b) Load current; c) Estimated load current

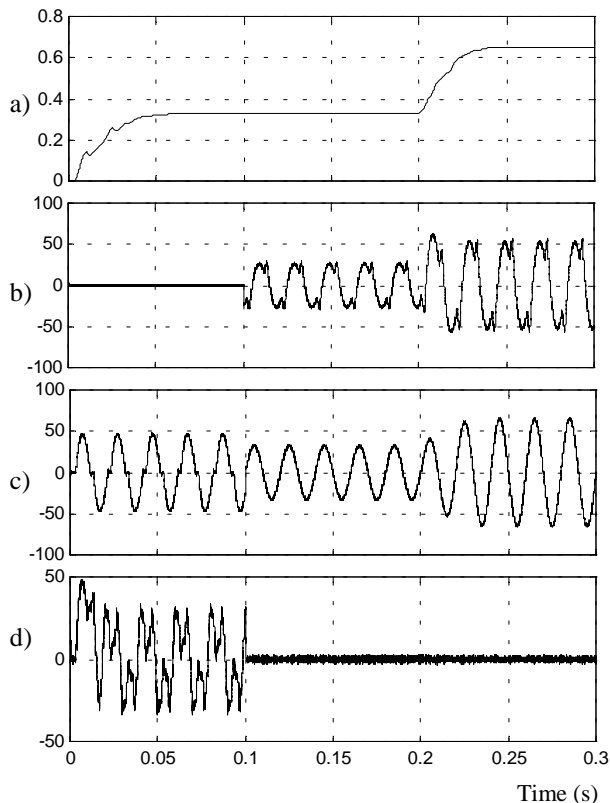


Figure 15: Case 2. Three-phase ac-regulator. a) Estimated equivalent conductance; b) Compensation current; c) Source current; d) Neutral source current

6 CONCLUSIONS

A new control method of an APLC has been presented. The control method is designed with two ANNs blocks. The first one includes Adaline networks, which estimate load voltage and current harmonic components. A new method to get fundamental active currents and reference compensation currents has been presented. In the hysteresis band control used, the usual comparators have been substituted by Feedforward networks trained by the backpropagation algorithm. The use of neural technologies presents advantages with regard to classical solutions, it increases the control speed and reliability. The results of two practical cases in Matlab-Simulink have been presented. The control design proposed allowed to get an excellent filter dynamic response to load changes. Nowadays, the authors are developing a practical implementation with dSpace software. A controller-board with a real-time processor allow to carry-out the control operation.

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