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Active power filter control using neural network technologies

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Abstract: A method for controlling an active power filter using neural networks is presented. Currently, there is an increase of voltage and current harmonics in power systems, caused by nonlinear loads. The active power filters (APFs) are used to compensate the generated harmonics and to correct the load power factor. The proposed control design is a pulse width modulation control (PWM) with two blocks that include neural networks. Adaptive networks estimate the reference compensation currents. On the other hand, a multilayer perceptron feedforward network (trained by a backpropagation algorithm) that works as a hysteresis band comparator is used. Two practical cases with Matlab-Simulink are presented to check the proposed control performance.

1 Introduction

Frequently, AC electrical power systems include several kinds of nonlinear loads (rectifiers, inverters, AC regulators, etc.). Thus load currents and voltages are nonsinusoidal, and it is necessary to compensate the voltage and current harmonics. In this case, it is possible to use active power filters (APFs). The use of shunt APFs is a method developed to suppress current harmonics and to correct power factor, especially in fast-fluctuating loads [1–4]. The target is to obtain balanced and sinusoidal source currents by injection of compensation currents.

The configurations of the APF power circuits developed include three-phase single-phase topologies. In symmetrical circuits a three-phase bridge inverter is suitable. However, in serious asymmetrical circuits, three single-phase bridge inverters have been used (i.e. each phase must be compensated individually). Here, the authors propose an APF with a three-phase IGBTs bridge converter with a split capacitor on the DC side, to compensate a three-phase unbalanced nonlinear load [4]. A control block allows trigger signals of switching devices used at the APF power circuit to be obtained.

The APF control has two main blocks: the first one generates the control reference signals and the second one carries out the control method. For three-phase four-wire systems, Akagi and co-authors introduced the so-called 'p–q–0' theory based on the 'α–β–0' transformation [5]. Recently, control reference currents have been obtained without mathematical transformations [6]. On the other hand, the control strategies of current controllers can be classified as ramp and hysteresis band comparators. The ramp comparator method compares the error between the actual and the reference compensation currents with a triangular waveform to generate the inverter firing pulses. The advantage is that inverter switching is limited to the frequency of the triangular waveform; however, there are phase and amplitude errors, steady-state included [7]. In the hysteresis band controller method, the currents will stay in a band around the reference currents; this scheme provides excellent dynamic performance. In this paper, a shunt APF with hysteresis band control is used to compensate the nonlinear loads.

Artificial neural networks (ANNs) have been systematically applied to electrical engineering [8, 9]. Nowadays, this technique is considered as a new tool for designing APF control circuits. The ANNs present two principal characteristics. It is not necessary to establish specific input–output relationships, but they are formulated through a learning process or through an adaptive algorithm. Moreover, parallel computing architecture increases the system speed and reliability [10–14].

In this paper, a new design of an 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 into the power system.

A new method for controlling an active power filter with artificial neural networks (ANNs) is presented and the ANNs blocks will be described. It will be shown how the electrical system and its compensation can be simulated in a Matlab-Simulink application. The results of two practical cases will be presented: compensation by shunt APF of a three-phase unbalanced AC regulator and compensation of a controlled three-phase converter.

2 Active power filter with neural networks

A system with a nonlinear three-phase load supplied by a voltage source is considered. A shunt active power filter is used to generate the compensation current. The nonlinear 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 source current without harmonic and reactive components. The suitable compensation current injected by the shunt APF corresponds to the load current nonactive component. The APF power circuit proposed is a three-phase IGBTs bridge inverter with a split capacitor in the DC side, to compensate

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for three-phase, four-wires, unbalanced nonlinear loads [4] (Fig. 1).

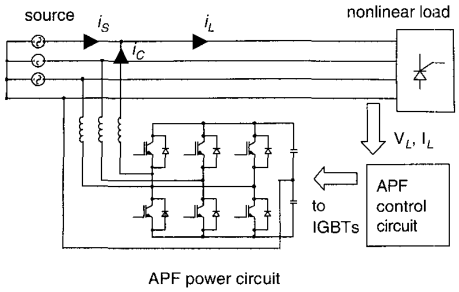

Fig. 1 *Three-phase four-wire system with shunt active power filter*

In this paper, a shunt APF with a hysteresis band control is used to compensate for the nonlinear loads. The target is to control the compensation currents by forcing them to follow the reference ones. The switching strategies of the three-phase inverter will keep the currents in the hysteresis band.

A control block generates the IGBTs trigger signals. A basic scheme for the proposed hysteresis band control is shown in Fig. 2. The real load currents are sensed and they are compared with their nonactive components, the reference compensation currents.

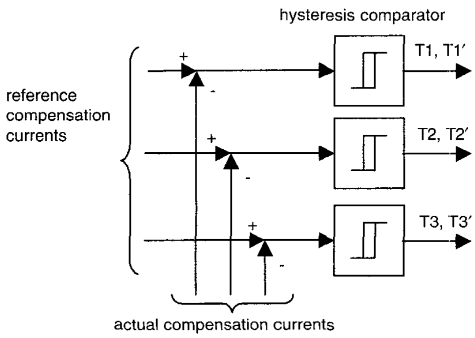

Fig. 2 *Hysteresis band control diagram*

The hysteresis comparator outputs signals are used to turn on the inverter power switches. The compensation current will stay in a band around the reference signal.

A new design of an APF control method based on neural networks is presented. Load voltages and currents are sensed, the control block calculates the power circuit IGBT trigger signals from the reference compensation currents, and the power circuit of APF injects the compensation current into the power system.

The control has two blocks. The first one is developed with adaptive networks (Adaline neurons), which allow on-line estimation to be made of control reference compensation currents. The second one is a feedforward network. After a training process, it works on-line as a comparator between the reference waveforms and the actual compensation currents (Fig. 3).

The first block inputs are load voltages ($v_{L,actual}$) and load currents ($i_{L,actual}$). This block estimates the compensation currents that are going to be used as reference in the control system ($i_{C,ref}$). The second block inputs are the differences between the actual and the reference compensation currents, the signals *Error* in Fig. 3. The actual compensation currents are the result of controlling the switching logic of power circuit transistors.

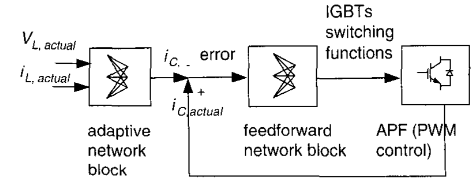

Fig. 3 *Block diagram of active power filter control*

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 the sum of the cosine and sine frequency components. The following model of the signal to be estimated is proposed:

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

where X_N and Y_N are the amplitude of the cosine and sine components of order-n harmonic. In vectorial notation:

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

where:

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

The signals are sampled at a uniform rate Δt, so time values are discrete, $k\Delta t$ with $k = 0, 1, 2 \ldots$. The dot product presented in (2) is carried out by one Adaline neuron, where $\mathbf{W}^T$ is the network weights vector. After the initial estimation, an adaptive algorithm updates the weights. Thus, the estimated signal converges to the actual one. Fig. 4 shows the network topology and the weights update algorithm. At time k, $\mathbf{x}(k)$ is the proposed signal model and $f_{actual}(k)$ is the actual signal. The neurons, taking into

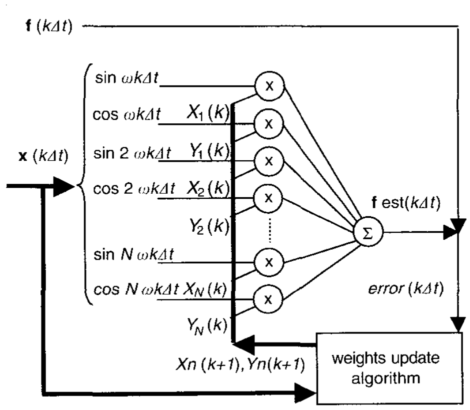

Fig. 4 *Adaptive network topology*

account their weights $\mathbf{W}(k)$, carry out an estimation $f_{est}(k)$. The error $e(k)$ is the difference between the actual signal and its estimation. An algorithm allows the weights to be used in the next iteration $\mathbf{W}(k+1)$ to be obtained, which minimises that error. After this iterative process, the estimated signals adapt to the actual signals.

The weight adaptation algorithm is a modification of the Widrow–Hoff (W–H) algorithm [13, 14], which minimises the average square error between the actual and the estimated signals. It can be written as follows:

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

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 the W–H rule can be written as follows:

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

In (5), $\mathbf{y}(k)$ is the $\mathbf{x}(k)$ sign, $\mathbf{y}(k) = \mathrm{sgn}(\mathbf{x}(k))$. As $\mathbf{x}(k)$ are sinusoidal signals, if the 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, which reduces the convergence problems introduced.

$$y(k) = 0.5 \cdot \mathrm{sgn}(\mathbf{x}(k)) + 0.5 \cdot \mathbf{x}(k) \tag{6}$$

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

$$\alpha = \alpha_0 + c_1 e + c_2 \dot{e} \tag{7}$$

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

Both corrections influence the convergence in opposite ways; this commitment must be achieved in order to get stable and fast enough convergence. The initial evolution of estimated signals depends on the initial choice of weight. Evolution from another change does not depend on that initial choice.

3.2 *Estimation of voltage and current waveforms*

As nonlinear loads are present in a power system, load current waveforms are nonsinusoidal. A periodic waveform can be expanded by Fourier analysis as the sum of the cosine and sine frequency components. So, load voltages and currents can be expressed as shown in (8) and (9):

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

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

where ω is the fundamental frequency, V_{n1} y V_{n2} are the cosine and sin frequency components of load voltage and I_{n1} and I_{n2} are the cosine and sin frequency components of load current.

Two Adaline neurons estimate the fundamental components of load voltage and current per phase. 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. The target source active current per phase is:

$$i_{act,r} = \frac{P}{V^2}\mathbf{v}_{r,1} = \frac{\frac{1}{T}\sum_{i=r,s,t}\int_0^T v_{i,1}i_{i,1}dt}{\frac{1}{T}\sum_{i=r,s,t}\int_0^T v_{i,1}^2 dt}\mathbf{v}_{r,1}$$
$$\Rightarrow i_{act,r} = \frac{\sum_{i=r,s,t}\langle v_{i,1}i_{i,1}\rangle}{\sum_{i=r,s,t}\langle v_{i,1}v_{i,1}\rangle}\mathbf{v}_{r,1} \tag{10}$$

The result of (10) is:

$$i_{act,r} = \frac{\sum_{i=r,s,t}(V_{i,11}I_{i,11} + V_{i,12}I_{i,12})}{\sum_{i=r,s,t}(V_{i,11}^2 + V_{i,12}^2)}(\mathrm{V}_{r,11}\cos(1\omega t) + \mathrm{V}_{r,12}\sin(1\omega t)) \tag{11}$$

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

$$i_{C,ref,r} = i_r - i_{act,r} \tag{12}$$

The source currents of compensated system become balanced and sinusoidals.

4 Control of compensation currents

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 Fig. 5.

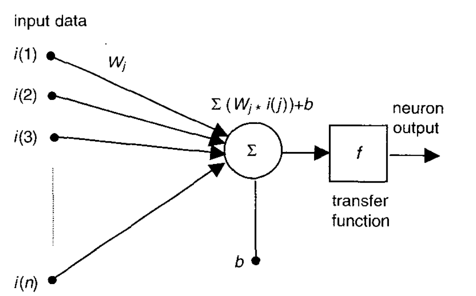

Fig. 5 *Artificial neuron model*

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

The neurons are connected conforming in different layers. A multilayer perceptron network has feedforward artitecture, as shown in Fig. 6.

The neural architecture consists of three layers: the input one, the hidden one and the output one. The circles represent neurons. There is a neuron in such an output. Thus, the feedforward architecture computes the input data in a parallel way, faster than the computer sequential

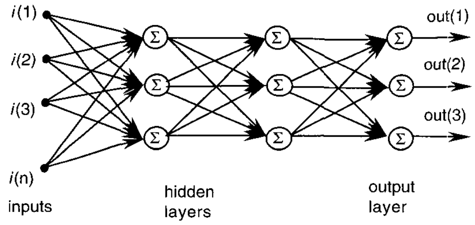

Fig. 6 *Feedforward neural network architecture*

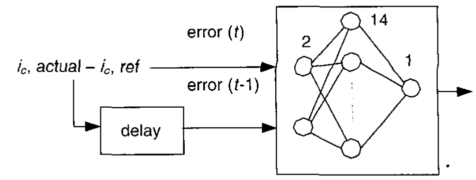

Fig. 7 *Topology of feedforward network*

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 from experimental results.

4.2 Neural PWM control

A feedforward neural network works as hysteresis comparator in the PWM control (Fig. 4). 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 k and its value in the previous time $k-1$. Network topology is shown in Fig. 7.

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

5 Results of practical cases

To check the proposed design, the electrical system, with control block included, was simulated in a Matlab-Simulink application. A three-phase sinusoidal source, a model of a three-phase AC regulator and the power circuit of an active power filter were developed in the same application, computer-aided by a power system blockset, to obtain the load voltages and currents of the electrical system. In Fig. 8, the Simulink diagram of a complete compensatory electrical system is shown.

The control block is presented in Fig. 9. An adaptive network block estimates the load voltages and currents. The difference between the actual currents and their estimated active components is the nonactive current used as reference compensation currents. On the other hand, the feedforward block works on-line as the hysteresis comparator, their inputs are reference and actual compensation currents, and their outputs are the trigger signals of power circuit IGBTs.

To train the feedforward network, it is necessary to know the real system input and output signals. So, the electrical system was simulated in Simulink, using a relay block as a comparator to obtain inputs and target-output signals. To train the feedforward network, the Matlab neural networks toolbox was used. A training programme using Matlab routines was developed. *Initff* initialises Network weights and *Trainlm* carries out the training process to fix the final

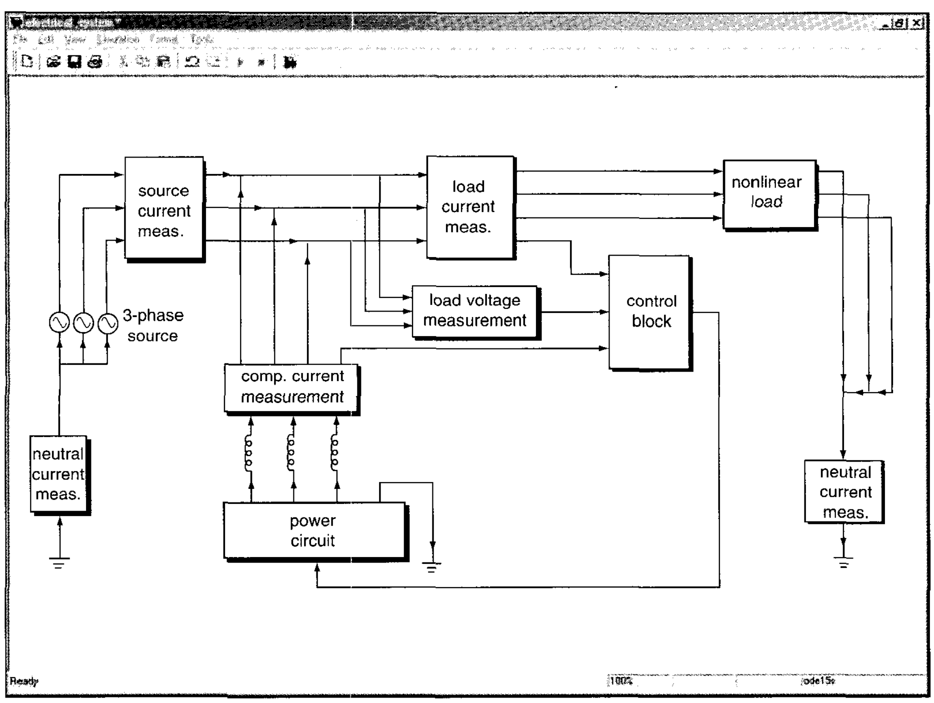

Fig. 8 *Simulink diagram of electrical system*

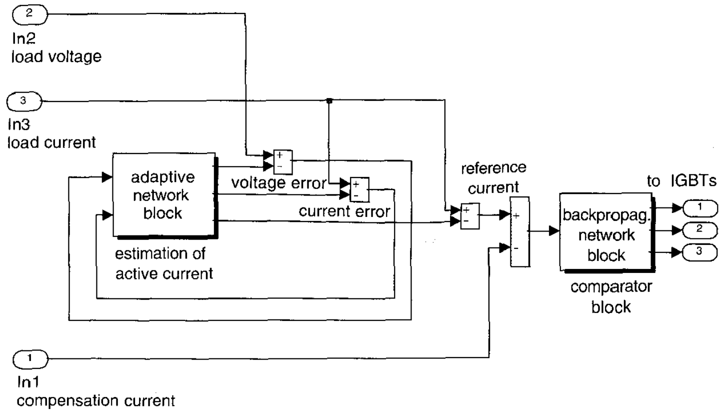

Fig. 9 *Simulink control block*

weights using pattern signals. After the training process, *Simuff* allows the network to work on-line as a comparator. The error of this comparator block was specified at 0.1% as a maximum goal. The error signal during the training process is shown in Fig. 10.

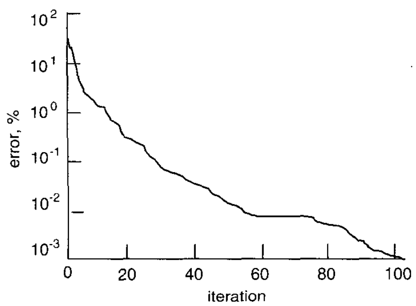

Fig. 10 *Error during training process*

The proposed design was applied in a three-phase four-wire power system, a three-phase balanced and sinusoidal voltage source supplying a nonlinear load, a controlled three-phase converter.

The electrical system has been simulated in a Matlab-Simulink application. Next, the evolution of several waveforms per phase from full load to 50% load is shown. Fig. 11(*a*) presents load voltage; actual and estimated load current are shown in Fig. 11(*b*) and 11(*c*).

The estimation of equivalent conductance (Fig. 12(*a*)) shows the transient evolution of process. The compensation current (Fig. 12(*b*)) is the result of hysteresis band control used. Fig. 12(*c*) presents the source current of the compensated system.

Signal evolution depends on the initial weights of adaptive networks. Those weights have been chosen as null in this example. The dynamic filter response is one-and-a-half periods approximately.

On the other hand, a second practical case was simulated, an unbalanced three-phase AC-regulator. As above, Figs. 13 and 14 show the main waveforms of this case: the load voltage, the load current, the estimated load current, the estimated equivalent conductance, the compensation current and the source current. The neutral current is null in the compensated system (Fig. 14(*d*)).

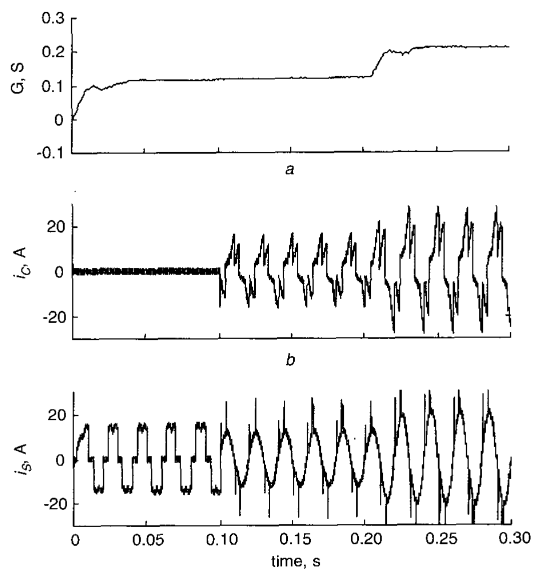

Fig. 11 *Case 1: Controlled three-phase converter compensation*
(*a*) load voltage
(*b*) load current
(*c*) estimated load current

At the moment, the practical implementation of ANN boards is not well developed. However, the authors are working to obtain a practical system, which allows the ANN proposed control to be emulated. The controller board developed by dSPACE contains a real-time processor and the necessary in/out interfaces to allow the control operation to be carried out. In particular, the DS1103 PPC controller board is equipped with a PowerPC processor for fast floating-point calculation at 400 MHz. This hardware supports the real time interface (RTI) tool that allows programming to be done *via* Simulink. The RTI carries out the real time code generation, it downloads the real-time model in the controller board and makes it start. Next, this will allow the experimental performance of the proposed control to be checked with this hardware.

6 Conclusions

A control method of an active power filter has been presented. The PWM control is designed with two neural

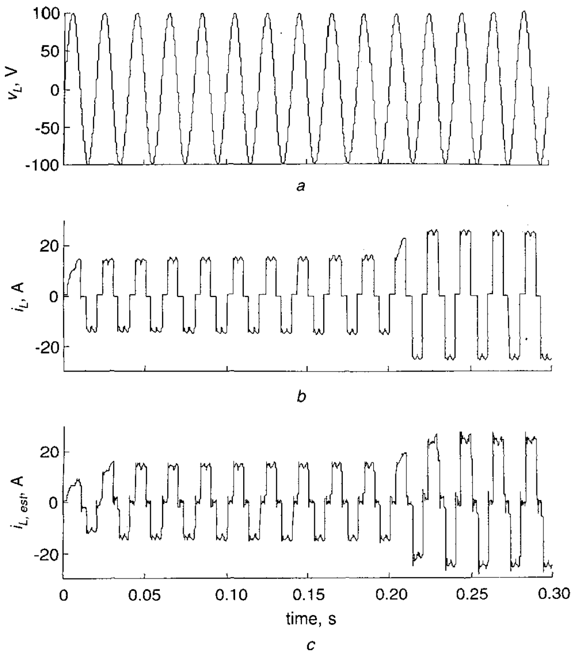

Fig. 12 *Case 1: Controlled three-phase converter compensation*
(*a*) estimated equivalent conductance
(*b*) compensation current
(*c*) source current

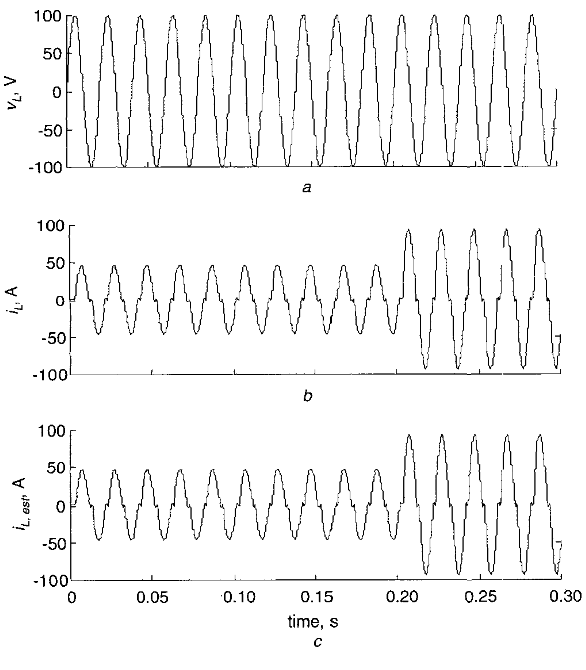

Fig. 13 *Case 2: Three-phase AC-regulator compensation*
(*a*) load voltage
(*b*) load current
(*c*) estimated load current

network blocks. The first one has two adaptive neurons, which estimate load voltage and current components. A simple method for obtaining fundamental active currents and reference compensation currents has been described. In the hysteresis band control used, the common comparators have been substituted by feedforward neural networks with

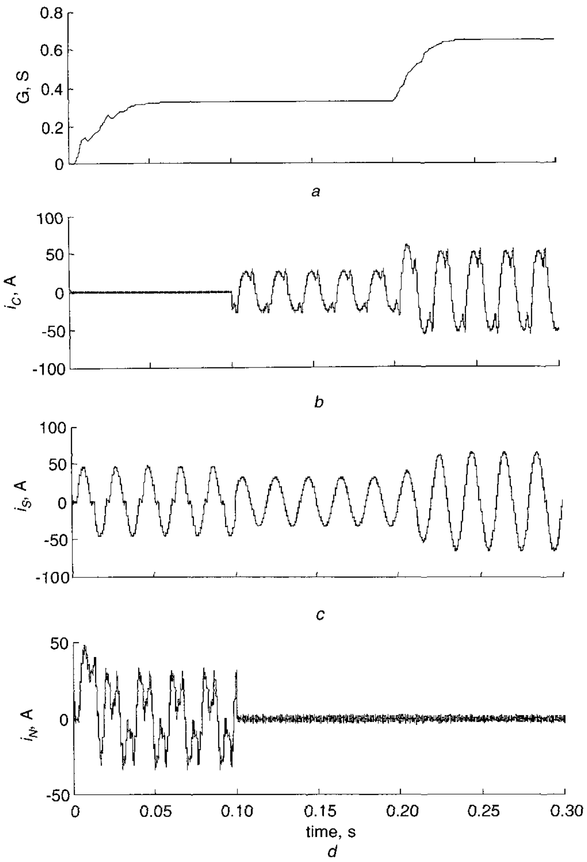

Fig. 14 *Case 2: Three-phase AC-regulator estimation*
(*a*) estimated equivalent conductance
(*b*) compensation current
(*c*) source current
(*d*) neutral source current

three layers trained by the backpropagation algorithm. The use of neural principles has increased the control speed and reliability by the new parallel computing architecture. The results of a practical case simulation in the Matlab-Simulink application have been presented. The control design proposed allowed an excellent filter dynamic response to load changes to be obtained.

7 Acknowledgments

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