Control of an active power filter using dynamic neural networks

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Abstract. At this paper the "dynamic multilayer perceptron" (MLP) neural network has been applied to the control of an active power filter (APF). The objective is developing a new suitable control technique by APF's for compensation of harmonic distortion present in nonlinear loads current by electric power circuits. The strategy has been extracting the instantaneous value of the fundamental harmonic from the load current by means of this artificial neural network (ANN) topology. A previous training with waveforms distorted by harmonics up to the 29th order showed to be enough for a high accuracy, working with typical nonlinear loads. By using this fundamental harmonic, the shunt APF reference distortion signal is obtained. This has been applied, at simulation, to a practical case of a power circuit containing an AC regulator and a series RL load. The results show the ability of this type of ANN to supply the APF with the reference signal necessary for its control.

Key words

Harmonics, Artificial neural network, Active power filter, Electric power quality.

1. Introduction

In the last years the high increase of problems in the electric power distribution networks due to the presence of harmonics has become well known. Loads that use switching control with semiconductor devices are the main cause. At the moment, one of the most important tools for correcting the lack of electric power quality are the active power filters (APF), that, thanks to the recent development of signal processing and power converters, are a growing reality. A good amount of effort are being made trying to find better solutions for the control and application of APF's to electric power networks.

The objective of this work has been proving that dynamic neural networks, such as the dynamic MLP topology, previously trained with a certain number of distorted waveforms, are an alternative to the rest of the techniques used and proposed at the present time for controlling of the APF's, as the ones based on the use of the Fast Fourier Transform (FFT). A large number of these control techniques are based on ANN's [1]-[9].

Fig. 1 shows a three-phase diagram of an ANN-controlled shunt APF. A load current signal $\boldsymbol{i_L}$ is acquired and used by the ANN to obtain the distortion current waveform as reference signal for the control of the APF. The power converter injects the necessary compensation current $\boldsymbol{i_C}$ in the power circuit, achieving thus a sinusoidal source current.

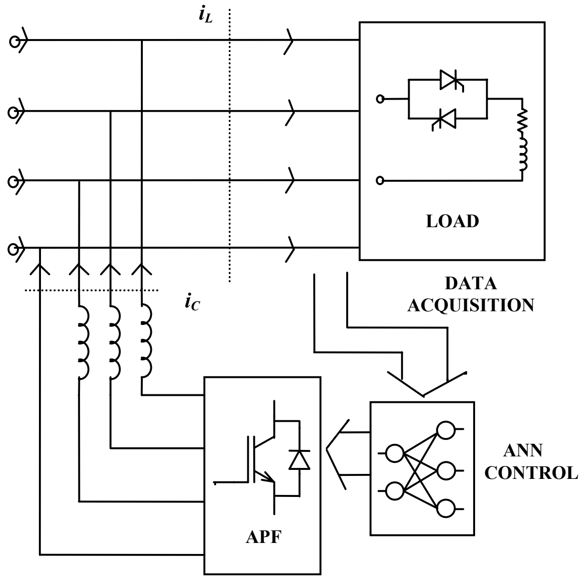

Fig. 1. ANN-controlled APF.

A good deal of effort has been made to apply neural networks with "off-line" training to the control of the APF's [1]-[7]. Some previous works showed the ability of different neural network topologies to be trained in this way for obtaining the distortion component of a waveform: the static MLP allows to obtain the amplitudes of the rectangular components of the harmonics (or another parameters) [1]-[4],[10]-[13]; different types of recurrent ANN's, such as Elman networks, can be used for extracting the fundamental harmonic of the waveform [5],[10]; and the dynamic MLP was also employed to get the distortion component [6],[14]. However, limitations are always present by their application to control an APF for different reasons: limitated number of harmonics, limitated accuracy, difficulties for training, the noisy environment, or hardware difficulties. Therefore it is justified to continue to look for new methods and better results, that could make able in the future a more common application of the ANN's for this purpose, with their advantages in terms of simplicity and dynamical performance.

At this paper, the strategy has been employing the dynamic MLP to get the instantaneous value of the fundamental harmonic in real time by introducing the acquired signal sequentialy into the ANN. The distortion current is hence obtained as the difference between the load current signal and its fundamental component, as can be seen in Fig. 2.

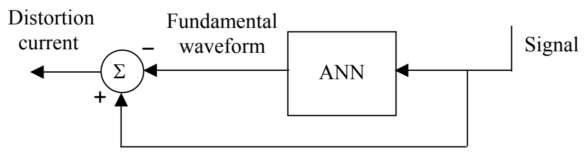

Fig. 2. Fundamental waveform strategy.

After an analysis of the different possible strategies and ANN topologies, this method with dynamic MLP achieved a high performance, extracting with a high accuracy and a low number of neurons the fundamental harmonic of distorted waveforms. It was considered the most suitable topology and method. Therefore, it has been used at this work to control the APF by the current harmonics compensation at a typical nonlinear load consisting of an AC regulator and a series RL load. So at this paper, two different steps can be noticed: the design and training of the ANN, and the simulation of the power circuit compensated with the neural network controlled APF.

2. Dynamic Multilayer Perceptron

An artificial neural network is the interconnection of processing units (artificial neurons) as the one showed y Fig. 3.

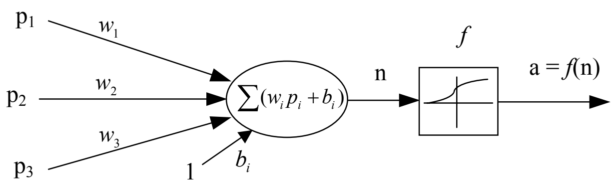

Fig. 3. Components of an artificial neuron.

The most common combination function used with the weighted inputs is the addition. And the following transfer function *f* applied can be linear or nonlinear. The linear function used in some of the neurons at this topology is

$$a = n \tag{1}$$

and among the different nonlinear functions [15],[16], the one used at this topology has been a sigmoidal type called "tan-sigmoid", that corresponds to the expression:

$$a = \frac{2}{1+e^{-2n}} - 1 \tag{2}$$

Neural networks are organized into layers of neurons. All neurons in a layer have the same transfer function. There is also the so called "input layer", formed by input units where the data stay until they are processed by the neurons. The number of layers can be two, three or higher. Fig. 4 corresponds to a simplified dynamic MLP topology that contains only 3 input units and 2 layers of neurons.

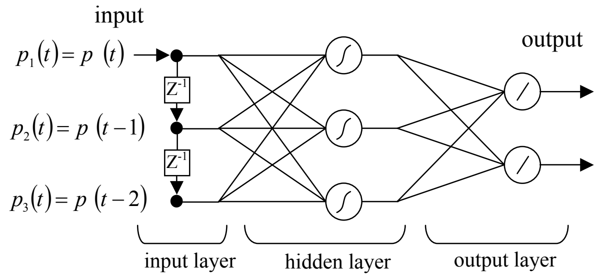

Fig. 4. Dynamic MLP network.

The transfer functions used are nonlinear in hidden layer and linear in the ouput one. At this work, the functions are tan-sigmoid and linear, respectively. And as can be seen in Fig. 4, the input layer to the neural network is a time delayed series of input signal values. The first input unit receives the instantaneous value of the signal, sequentially introduced. The other input units have the delayed values of the input signal. This feature gives to the network the property of "short-term memory" [17], what makes it specially useful for the extraction of the instantaneous value of the fundamental harmonic in real-time, then they always store the last cycle values of the signal.

The design of the neural network consists of the adjusment of the number of layers, the number of elements in every layer and the choice of the transfer function to employ in the hidden layers. After that, the network is trained by means of "backpropagation" algorithm and some sets of training pairs consisting each of a distorted waveform and its corresponding fundamental harmonic, with the aim of adjusting the connection weights of every neuron. At this point, the ANN should be ready for use.

3. Design and training of the ANN

The objective consists of obtaining a neural network able to extract with enough accuracy the fundamental harmonic from waveforms distorted by a large number of harmonics.

A. Accuracy

As regards the accuracy, this must be high enough to ensure a correct load current compensation in a power circuit.

The accuracy of the ANN output will be measured in terms of the "mean square error" (mse). Being the error the difference between the neural network output signal and the real fundamental harmonic of the input waveform. This mean square error constitutes the mean value of the squared errors at every sample point along a cycle of the fundamental harmonic (128 points, as will be seen later).

For evaluation of the neural network accuracy, the mse obtained by the generalization will be considered. It means, the evaluation index will be the mse of the ANN output for input waveforms that are distorted by several of the harmonics employed by the training, but in combinations that are different of those used as training waveforms. Another accuracy test will consist of the mse in the case of waveforms distorted by a larger number of harmonics than used at the training, with the aim of evaluating the neural network tolerance to higher order harmonics. In general, an mse = 1E–3 will be established as maximum allowable error by waveforms with unit amplitude in their fundamental component.

B. Number of harmonics

As regards the harmonics number, that the ANN has to be able to correctly manage, it depends on the expected load types where the APF will be employed. The established goal is the elimination of harmonics from 3^{rd} to an order higher than 20^{th}. Although a much higher order than 20^{th} can be reached under certain conditions.

It has been proven, that with the necessary sampling frequency for the correct function of the APF, and by short training times of the order of an hour by a current personal computer, the allowed number of harmonics by the training lies about 10. Having into account that in typical nonlinear loads the presence of even harmonics is very low, for a single-phase circuit the harmonics used would be the odd ones from the 3^{rd} to the 21^{st}. Considering a three-phase circuit, where the triplen harmonics can be ignored, the components to use would be the orders 5, 7, 11, 13, 17, 19, 23, 25 and 29.

If required, in case of loads that generate a wide spectrum harmonic distortion, the ANN could be adjusted for eliminating several additional harmonics by means of longer training times: increasing the number of training waveforms and the number of neurons in hidden layer.

C. ANN design

For the suitable neural network design, results of previous works have been considered, where it was proven that a single hidden layer was necessary with a very low number of neurons (3 elements by trainings with 4 harmonics) and a nonlinear "tan-sigmoid" type transfer function [10]. In the output layer, due to the nature of the strategy, only one neuron was required, then it consists of a single sequential output of the instantaneous value of fundamental harmonic. Two hidden layers, or some additional neurons in network, cause increased training times with no better results for the same sets of harmonics. And finally, with regard to the hidden layer transfer function, less accurate results were obtained, when another functions were employed.

For a training with more harmonics (9 or 10) the number of neurons in hidden layer had to be increased up to an adequate number of 5 elements. As regards the number of input units it has been required a sampling rate of 128 samples every fundamental harmonic cycle, what means that the input layer consists of a single actual data input and 127 time-delay input units. With a lower sampling frequency, such as 64 samples per cycle, the ANN can also be correctly trained, but its resultant output is a series of steps with a step width too large for the aim of application to the APF. The described neural network, that has been used at this work, can be seen in Fig. 5.

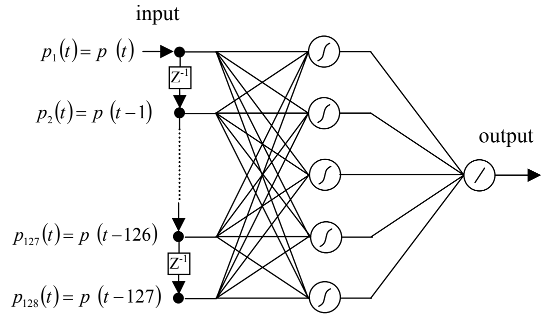

Fig. 5. Dynamic MLP network applied to the APF.

D. Training

The training of the above shown ANN was carried out with the "Neural Network Toolbox" of MatLab. The training algorithm used by all MLP networks is "backpropagation", and the special method in which this algorithm was computed was the "Levenberg-Marquardt" one.

Since the usual distorted current consists of the sum of harmonics shown in following equation,

$$i(t) = \sum_{n=1}^{\infty} \left[I_n sen(n\omega t + \varphi_n) \right] \quad (3)$$

for application of the training algorithm a certain number of waveforms, with this equation generated, has been employed. Each of them contains a fundamental amplitude $I_1 = 1$ and a determined combination of the rest of the odd harmonics from 3^{rd} to 19^{th} (9 harmonics have been used for the results presented at this paper), with amplitudes 20% of that of the fundamental one, it means, with a value of 0.2. Every phase was set to $\varphi_n = 0$. The amplitude values have been set to the order of the unit because a better training is possible, being later the current signals normalized by the application of the ANN to the APF.

A total number of 32 different waveforms has been necessary for a correct training. The associated output for each of them corresponds to the fundamental harmonic they contain.

By applying this 32 training pairs to the neural network with the use of backpropagation algorithm, all interconnection weights are conveniently adjusted. After several iterations during one hour, the network performance reached was of mse = 3E–5 as maximum error by the waveforms of training pairs.

E. Training results

An analysis of the neural network accuracy follows in this section. The results here presented show the ANN performance with different cases of distorted waveforms. In Table I it can be seen the harmonic content of the 5 waveforms selected for this test and also the resultant error mse of the neural network response. This table contains the amplitudes (A) and phases (Ph) for every harmonic order included in each of the waveforms.

In Fig. 6 to Fig. 10 it can be seen the results for the cases 1 to 5 of Table I. These figures show the waveforms introduced to the ANN and a comparison of the output and the real fundamental harmonic. At the first three cases, the error is so low that no difference can be appreciated at the corresponding figures between the ANN output and the fundamental component.

TABLE I.- ANN performance test: Harmonic content of 5 input waveforms with high distortion, and resulting error at the ouput for each of the cases (column at the right).

Input waveform case		I_1	I_3	I_5	I_7	I_9	I_{11}	I_{13}	I_{15}	I_{17}	I_{19}	I_{21}	I_{23}	I_{25}	Output error (mse)
1	**A**	1	0.2	0.15	0.1	0.05	0	0.2	0.15	0.1	0.05	0	0	0	2.0 E–7
	Ph	0	0	0	0	0	0	0	0	0	0	0	0	0	
2	**A**	1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0	0	0	1.4 E–5
	Ph	30º	0	60º	–30º	0	0	90º	0	–90º	0	0	0	0	
3	**A**	0.7	0.7	0.2	0.4	0	0.2	0.4	0.1	0.2	0.3	0	0	0	5.7 E–6
	Ph	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	**A**	1	0.2	0.2	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.2	0	0	5.1 E–4
	Ph	0	0	0	0	0	0	0	0	0	90º	90º	0	0	
5	**A**	1	0.2	0.1	0	0.2	0.1	0	0.2	0.1	0	0.1	0.05	0.05	9.5 E–4
	Ph	0	0	0	0	60º	0	0	0	0	90º	90º	90º	90º	

Case 1: This waveform contains a set of harmonics of the ones used at the training. They have no phase and their amplitudes are different from the ones employed at the training. However, their values are not higher than the 20% of the fundamental, it means, not higher than the values used at the training. Fig. 6 shows the elevated accuracy with this type of waveforms.

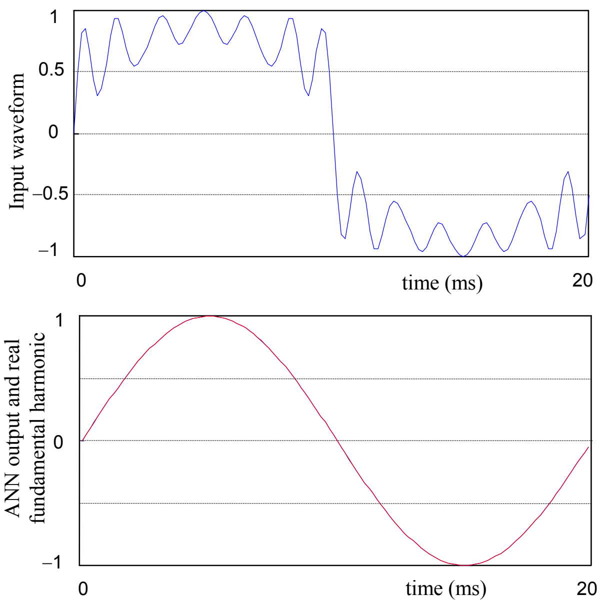

Fig. 6. ANN performance: case 1 of Table I.

Case 2: In this case, the ANN response is tested when some phases are present in their harmonics. The set of amplitudes corresponds to one of the waveforms employed at the training. In Fig. 7 can be seen that the ANN continues to work correctly in case of phases in the harmonics, despite no phases were used at the training pairs.

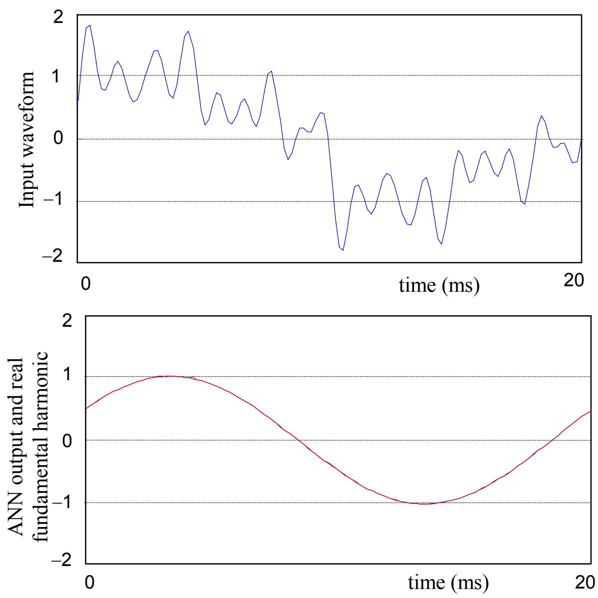

Fig. 7. ANN performance: case 2 of Table I.

Case 3: In this case it is tested the response when larger harmonic amplitudes than the ones used at the training are present in the waveform. The 3rd harmonic amplitude is even 100% of the fundamental component, much higher than the 20% used by the training pairs. In Fig. 8 the good response of the neural network in these cases can be observed.

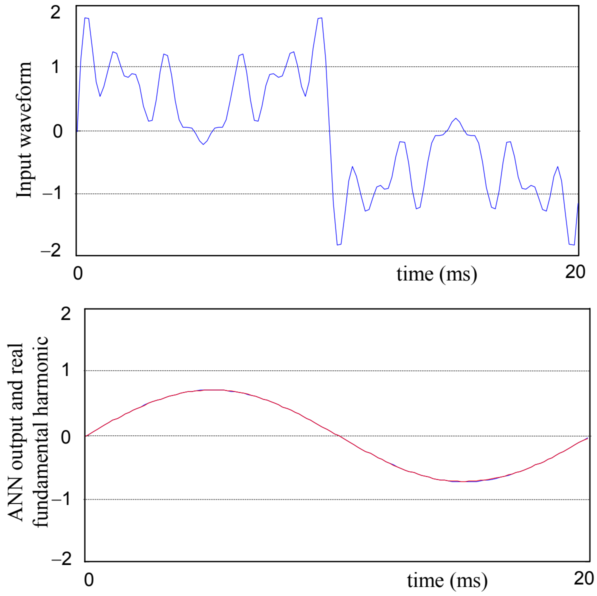

Fig. 8. ANN performance: case 3 of Table I.

Case 4: Once it was proven that the ANN generalization in amplitude and phase was very good by waveforms containing only the harmonics of the training, it is tested in case 4 the effect of higher order harmonics for evaluation of the network tolerance when harmonics, that were not considered at the training, are present. A 20% content of the 21st one and some phases are present in the waveform of this case. In Fig. 9 it can be observed that the ANN doesn't work with the same accuracy as before. However, once again its output error lies under the value 1E–3 established as goal, thus showing that at least the following harmonic order to those of the training is well tolerated.

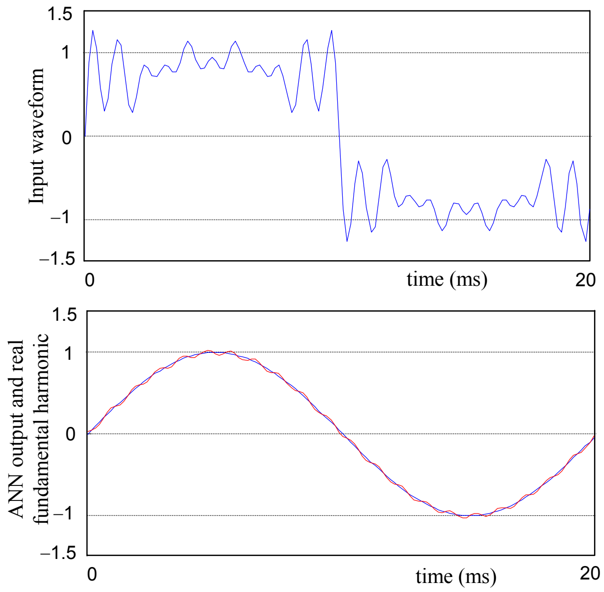

Fig. 9. ANN performance: case 4 of Table I.

Case 5: And finally, the result is presented in case of a waveform which contains small amounts of three of the higher order harmonics: 10% of the 21st, 5% of the 23rd and 5% of the 25th. In Fig. 10 it can be noticed that the network response is less accurate, being the error mse near the limit established as accuracy goal. But in spite of the larger influence of those harmonics on the error, it can be said that the ANN continues to reach its goal. That's to say, this neural network owns a certain tolerance by the presence of small harmonic amounts of higher order than the ones used at the training.

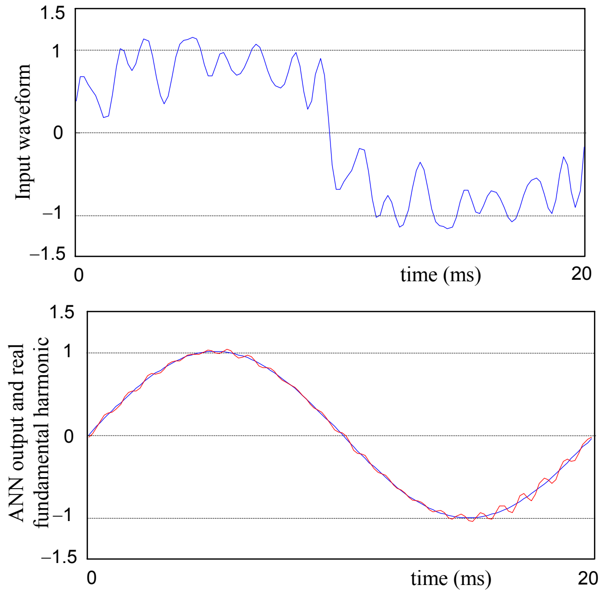

Fig. 10. ANN performance: case 5 of Table I.

4. Power circuit and active power filter

Once the design and training had been carried out, the resulting neural network is applied to the control of an APF by simulation with MatLab tools. The system consisted on a power circuit, an active power filter and the ANN controller, as can be seen at Fig. 11 in next page.

The voltage source in power circuit was taken without distortion, 220 V_{RMS} , 50 Hz frequency. The load consisted of an AC regulator, based on thyristors, and a series RL load. The APF is based on a bridge of IGBT's with a V_{dc} = 500 V. The ANN control corresponds to the diagram shown above at Fig. 2, where a sampling of the signal is made at a frequency of 128 samples/cycle (a sample every 1.5625E–4 seconds).

5. Simulation results

The model of Fig. 11 was simulated by using Matlab. Different sets of parameters were employed at the power circuit and APF. In most cases the reference current obtained by the ANN controller was accurate enough to enable the APF to compensate harmonic distortion.

Only in cases in which an elevated content of high order harmonics were present in the load current, the ANN controller failed in obtaining an accurate reference signal. But this may be improved with longer training times, increasing the number of harmonics present in the training waveforms and the number of neurons.

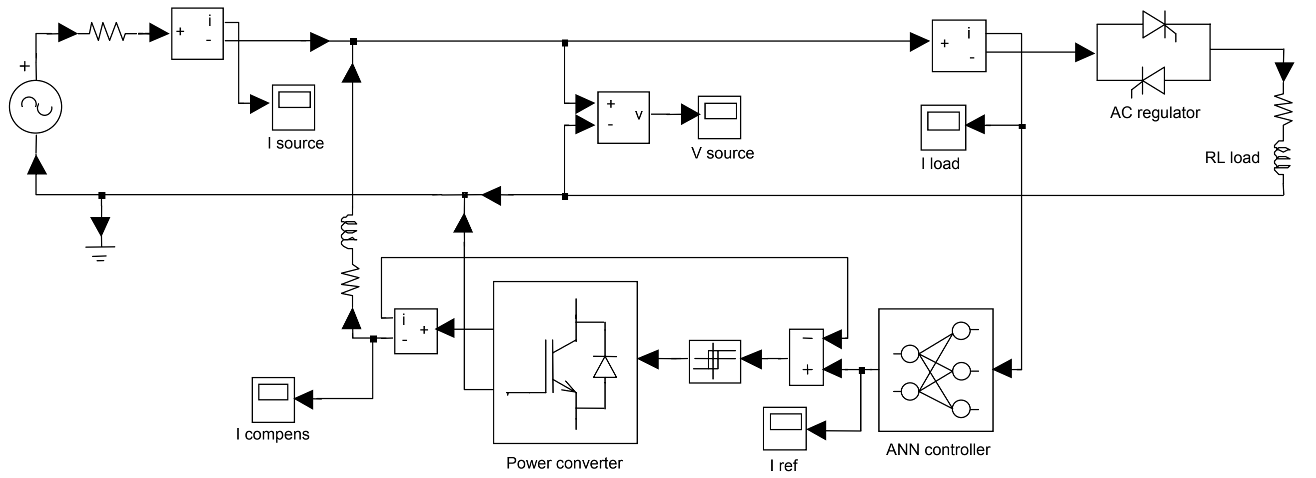

Fig. 11. Power circuit with active power filter and ANN control.

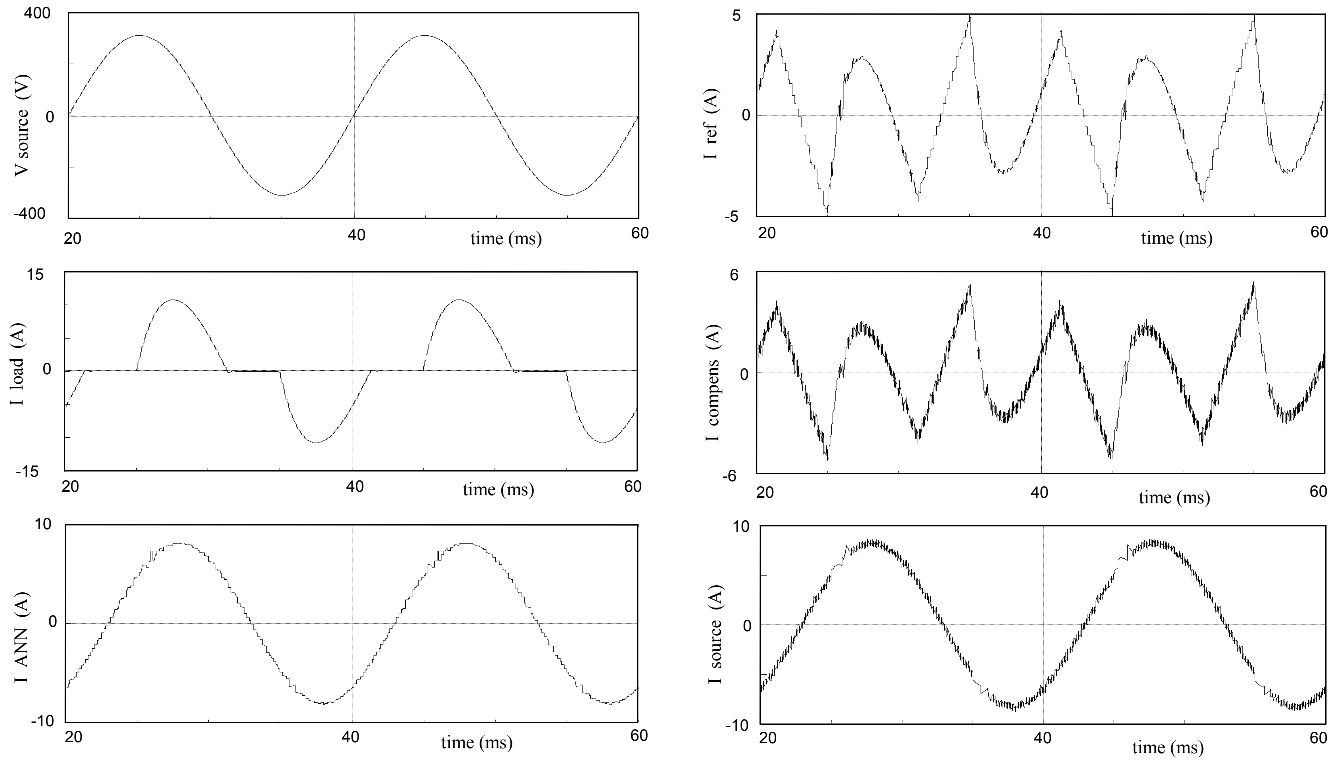

Fig. 12. Results of the typical circuit system of figure 11 simulated with parameters of Table II. They represent: source voltage, load current, output signal current of the ANN, reference current signal obtained by the ANN controller, APF output (compensation current), and resulting compensated source current.

Nevertheless, a high performance was obtained with this 6-neuron ANN, as can be seen in the results here presented. A list of the system parameters considered for this simulation is given in Table II.

A. Steady state harmonics compensation

The results for the practical system with parameters of Table II can be seen at Fig. 12: Source voltage, load current, instantaneous value of the fundamental harmonic obtained by the ANN, reference current obtained as the difference between load current and fundamental harmonic, compensation current injected by the power converter, and finally, the resulting source current.

TABLE II. System parameters used in simulation.

Power circuit:	Phase voltage = 220 V_{RMS} Frecuency = 50 Hz Source resistance = 0.1 Ω Load resistance = 20 Ω Load inductance = 30 mH
APF:	V_{dc} = 500 V R = 10 Ω L = 30 mH Switching frequency = 40 KHz

It is to notice that the harmonic distortion was fairly well eliminated, remaining as result a nearly sinusoidal waveform.

B. Dynamical performance

In order to test the performance of the ANN by load changes, the results of a simulation are here presented where a step load change occurs at time 60 ms. One additional resistance is connected in parallel with the load, as can be seen in Fig. 13, consequently increasing the total load current. Fig. 14 shows the effect of the change on the current, on the ANN output and on the source current. As can be observed, the neural network presents a fast respond, requiring only one cycle, 20 ms time, to give again the right value of the fundamental harmonic, with the corresponding compensation.

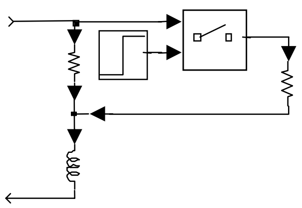

Fig. 13. Load change for transient response test.

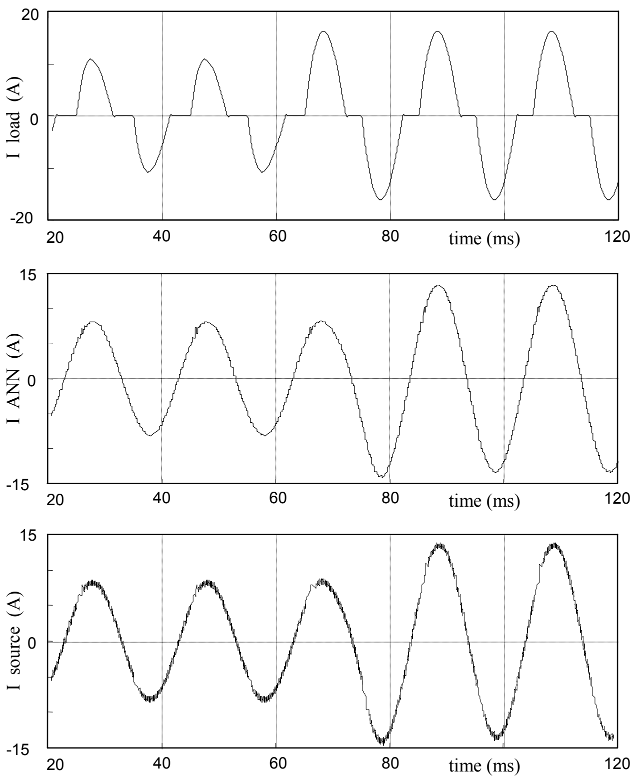

Fig. 14. Dynamical performance. Step load change at 60 ms, ANN ouput and compensated source current.

6. Conclusion

A dynamic multilayer perceptron ANN has been trained for its use at the control of a shunt active power filter. In previous works another techniques and network topologies or strategies were employed with variable results. In this work the dynamic MLP has been proven at the strategy of obtaining the instantaneous value of the fundamental component in harmonic distorted load current waveforms. Its "short-term memory" property due to the time-delay elements in its input layer makes it specially suitable for extracting in real-time this harmonic.

By off-line trainings with harmonic distorted waveforms, this ANN may be adjusted, with only 6 neurons and short training times, for an accurate working with a maximum harmonic order higher than 20^{th}. By means of longer traning times and some additional neurons, even a higher harmonic order can be achieved.

A practical case with a power circuit containing an AC regulator and a RL load, compensated with an APF controlled by one of these networks, has been simulated. Although the presence of very high order current harmonics by some particular loads might reduce the accuracy of the ANN's, the results obtained at this work show that this control method can be applied to an APF in case of typical loads with a high accuracy and a fast transient response by load changes.

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