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# Current Harmonic Estimation in Power Transmission Lines Using Multi-layer Perceptron Learning Strategies

Patrice Wira and Thien Minh Nguyen

*MIPS Laboratory, University of Haute Alsace, Mulhouse 68093, France*

**Abstract:** This main contribution of this work is to propose a new approach based on a structure of MLPs (multi-layer perceptrons) for identifying current harmonics in low power distribution systems. In this approach, MLPs are proposed and trained with signal sets that are generated from real harmonic waveforms. After training, each trained MLP is able to identify the two coefficients of each harmonic term of the input signal. The effectiveness of the new approach is evaluated by two experiments and is also compared to another recent MLP method. Experimental results show that the proposed MLPs approach enables to identify effectively the amplitudes of harmonic terms from the signals under noisy condition. The new approach can be applied in harmonic compensation strategies with an active power filter to ensure power quality issues in electrical power systems.

**Key words:** Power quality, harmonic identification, MLP (multi-layer perceptron), Fourier series, active power filtering.

## 1. Introduction

Since a couple of decades, the number of electrical nonlinear devices has increased continually in domestic and industrial installations. The unwanted harmonics generated by nonlinear loads or devices yield many problems in power systems [1]. Technical solutions like active power filters [2] implement harmonic identification algorithm approaches in order to compensate for harmonic distortions introduced by lots of modern electrical devices. This principle is presented by Fig. 1. Therefore, harmonic identification approaches are more important than ever for power quality issues.

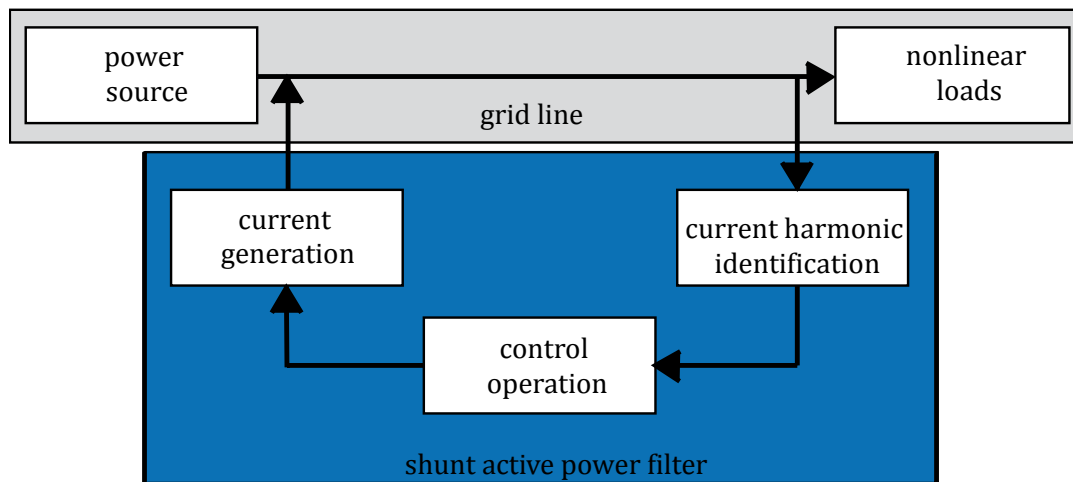
In a power system, a harmonic term is defined as a sinusoidal component of a periodic waveform. A harmonic component has a frequency value that is an integer multiple of the fundamental frequency of the power line. Many studies in harmonic distortion identification have been conducted in order provided tools able to improve the power quality in electrical systems. Different techniques from the signal processing field have been widely used for improving

the efficiency of electrical power supplies. For example, DFT (discrete Fourier transform), FFT (fast Fourier transform), TFDs (time-frequency distributions), TDAFs (transform domain adaptive filters), WTs (wavelet transforms), and IPT (instantaneous power theory) are well-known techniques that have been applied in electrical power systems for power quality enhancement [3-5]. All these methods can be used to analyze distorted waveforms from power lines. Thus, they can be inserted in a shunt active power filter strategy like the one depicted by Fig. 1. However, they represent a complicated process, the behavior of active filter is then delayed such that it is difficult to compensate harmonic in real-time. In order to improve the processing speed and simplify harmonic detection process, ANNs (artificial neural networks) are applicable to detect each harmonic effectively.

Recently, ANNs have been successfully used in power system applications [6]. With their learning capabilities, ANNs can learn from examples. Indeed, ANNs can provide a prospective way for solving complex and ill-defined problems. After training, they can perform generalization and prediction. In power systems, several successful neural approaches have been

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**Corresponding author:** Patrice Wira, Ph.D., professor in electrical engineering and computer science.



**Fig. 1** Typical structure of active power filter.

applied for voltage sags and swells detection, for fundamental frequency estimation, for compensation of power-quality disturbances and, of course, for the control [7, 8] and fault diagnosis [9] of motor drives.

Currently, the MLP (multi-layer perceptron) with the BP (back-propagation) training algorithm [10, 11] is the most widely used learning process in machine learning applications. This neural network has many advantages, among them nonlinear classification and pattern recognition abilities in real life applications.

This paper proposes a new neural approach for identifying electrical power system harmonics in order to provide a more effective solution for current harmonics compensation in power distribution systems. This approach is based on the MLP architecture which can be easily trained and is able to estimate the coefficients of the harmonic terms composing the Fourier series of the signal measured from the grid line. This method is able to be inserted in a shunt active power filter strategy. This is an important step in contributing to enhance power quality issues in power systems and smart grids.

In the remainder of this paper, Section 2 briefly reviews several other approaches based on ANNs for estimating the harmonic content of signals. Section 3 introduces the MLP principle, proposes a new approach based on MLPs to estimate the Fourier series

coefficients and presents how to get the individual harmonic terms. The results of computer experiments and comparisons are provided in Section 4. Finally, Section 5 concludes this paper.

## 2. Neural Network Methods for Harmonic Identification

ANN approaches have very good abilities to learn from sample data [12] and that is why they are excellent candidates for modern advanced digital signal processing tasks. In this section, several ANN approaches for harmonic identification are reviewed. They are based on the Adaline neural network, the MLP network, the RBF network, the RNN network and a linear MLP network.

The Adaline network is the simplest approach among all of neural techniques for estimating harmonics. An Adaline is only a single artificial neuron [12, 13]. Each Adaline has several inputs and returns one output. An Adaline neuron is called a linear neuron because it has a linear activation function or the identity function. This means that its output is a weighted sum of its input. The weights are computed from a training process based on the minimization of a mean squared error. In the context of harmonic identification, the coefficients of the fundamental and the harmonic components of the Fourier series are

represented by the weights of Adaline. There are several successful variants that have been developed [14]. Fig. 2 shows an example of Adaline network with oscillating terms as input [15] which is used to estimate the amplitudes and phase angle of harmonic terms.

As it has been previously mentioned, MLPs have also been proposed in various approaches. This network is the most widely used learning approach in commercial and industrial applications. The MLP takes a set of inputs in its input layer. All the neurons are organized in layers, from the input to the output layer there are one or more hidden layers. The data, i.e., the sampled signals, come into this network by the input layer, go through the hidden layers and come out of the network by the output layer. The data go from one layer to the other one by going through neurons. All the neurons use a weighting and an activation function to determine their output. MLPs have thus to be trained in order to adjust the weights that will give outputs as close as possible to some reference values. The BP is the most well-known training algorithm for adapting the weights of MLP networks [16]. MLP architectures for harmonic detection and identification in active filter schemes have been proposed in Ref. [17]. In this application, two types of MLP with the BP learning algorithm have been used. A fully connected and a partial connected MLP have been compared for detecting the 3rd and 5th harmonics. The amplitudes from one cycle distorted waveform are used as the MLP's inputs. The output layer of the network consists of output neurons corresponding to two harmonic components that need to be detected. Since, several other approaches for estimating harmonics with MLPs have been developed [18-21].

RBF (radial basis functions) neural networks are similar to MLP networks but the activation functions of their hidden neurons are radial basis functions and the activation function of the output neurons is a sum. Thus, the output of the network is a linear combination of radial basis functions of the inputs characterized by neuron's weights and biases. An RBF approach has

been proposed for the harmonic amplitudes detection of a signal in Ref. [22]. The RBF is able to approximate the mapping between the sample signal and the amplitude and the phase angle of each harmonic component. The RBF network must be trained off-line before using to estimate the harmonic components of a signal.

An RNN (recurrent neural network) is a kind of dynamical neural networks where the inputs of the neurons also come from the output neurons not only from the previous layers but also from the following layers. This network is therefore able to exhibit dynamic temporal behaviors because an internal network state that is created by the presence of feedback loops [23]. An RNN based approach for harmonic estimation has been introduced in Ref. [24]. In this work, feed forward and Elman's recurrent neural networks are used to detect harmonics from distorted signals including harmonics of ranks 5, 7, 11 and 13.

In Ref. [25], an approach based on a linear MLP to learn and estimate on-line the harmonics from measured signals has been proposed. The linear MLP is able estimate any periodic signal by expressing its output as a sum of harmonic components in the Fourier series. The network uses some generated oscillating signals as inputs and uses neurons with linear activation functions. The output of the network is a combination of combined oscillating signals and is compared to a measured signal that serves as a reference. The amplitudes of the fundamental and high order harmonics are deduced from the combination of the weights. The linear MLP identifies the amplitudes

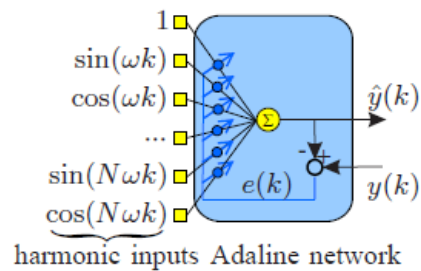


Fig. 2 Adaline architecture with harmonic terms as input.

of the fundamental component and high-order harmonic components with a good precision even under noisy condition. Fig. 3 shows the linear MLP with 5 neurons in one hidden layer for harmonic estimation. A different approach is investigated thereafter, with several MLPs and where each of them is devoted to one specific harmonic.

### 3. A New Multilayer Perceptron Method for Harmonic Identification

In this section, the architecture of a typical MLP is quickly presented and then we introduce a new learning structure based on several MLPs for solving the problem of harmonic identification.

#### 3.1 A Typical Multilayer Perceptron

MLPs are multilayer feed forward neural networks that can learn from training data sets and are effective for solving problems in nonlinear classification and pattern recognition [12]. The data go into the neurons of the network via the input layer, passes through the hidden layers and finally exits from the output layer.

In a typical MLP network, there are two kinds of artificial neurons, the hidden neurons and the output neurons. The hidden neurons are neurons that belong to the hidden layers. The output neurons are neurons that are located in the output layer. Typically, a hidden

neuron has a nonlinear activation function and an output neuron has a linear activation function. An MLP has only one output layer and can be composed of one or more hidden layers. Fig. 4 shows an example of a typical MLP with 5 neurons in one hidden layer and 3 neurons in the output layer.

Training the MLP consists in using a learning procedure in order to compute the weights of the neurons. The training is based on data examples that are called the training sets. The neural network training is realized by using BP algorithms. The BP algorithm family monitors the global error of the neural network and propagates the error during the training in order to adjust the weights of the neurons [10, 11, 26]. After finishing the training, the neural network is capable of estimating the nonlinear input-output relationship of the problem that needs to be solved.

#### 3.2 A New Structure Based on MLPs for Harmonic Identification

A new structure based on several MLPs with appropriate inputs and outputs is developed in order to provide a more effective method for solving the harmonic identification problem. In this work, the MLPs are trained by a signal samples and after training, MLPs are able to identify harmonic components in electrical power systems.

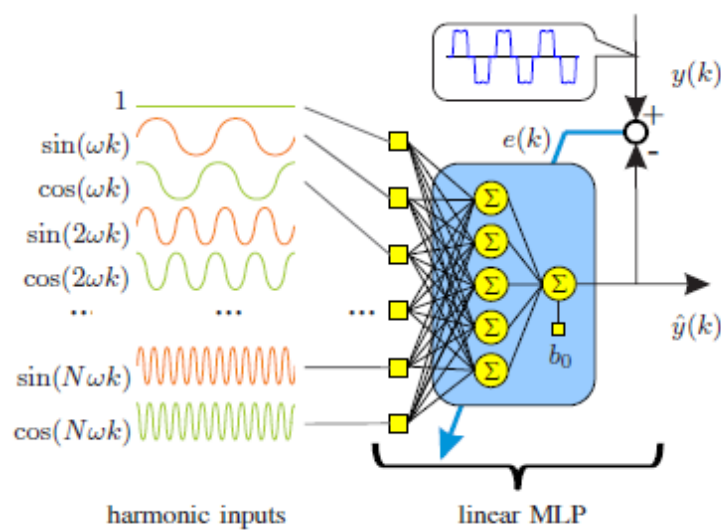


Fig. 3 A linear MLP with 5 neurons in one hidden layer for harmonic estimation.

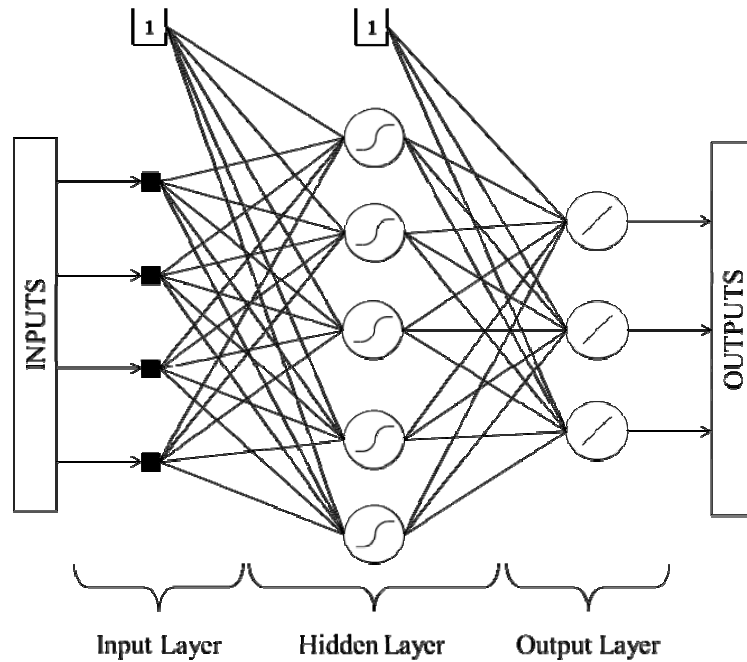


Fig. 4 Typical MLP architecture.

In the Fourier analysis, any periodic or distorted waveform/signal can be represented by a function  $f$  that is also called a Fourier series,

$$f(t) = A_0 + \sum_{n=1}^{\infty} [A_n \cos(n\omega t) + B_n \sin(n\omega t)] \quad (1)$$

where  $A_0$  is the DC (this stands for direct current) component, the sums of  $A_n \cos(n\omega t)$  and  $B_n \sin(n\omega t)$  mathematically represent the  $n$ -th waveform components, and  $n$  is called the order of the  $n$ -th waveform component.

In a Fourier series, the waveform component with  $n = 1$  is called the fundamental waveform component. If  $T$  is the period of the periodic signal,  $\omega = 2\pi / T$  is the fundamental angular frequency and  $f_0 = 1 / T$  is the fundamental frequency or the frequency of the fundamental waveform of the signal. Additionally, the waveform components with  $n > 1$  are called higher-order harmonic components or harmonics for more simplicity. Thus, every harmonic component is defined by two coefficients  $A_i$  and  $B_i$ .

The main idea of this method is to use an MLP network with two outputs to identify the two coefficients  $A_i$  and  $B_i$  corresponding to each harmonic component of a Fourier series. Each

harmonic is therefore estimated by a specific MLP network. Each MLP gets a first half fundamental period of the distorted waveform samples as input and provides the two coefficients of a harmonic component.

The way an MLP identifies a single harmonic component of the distorted signal is illustrated by Fig. 5. In this example, the MLP network has one hidden layer having several nonlinear hidden neurons and two linear neurons in its output layer. The MLP takes the samples from the distorted waveform in the first half of fundamental period as the inputs  $[x_1 \ x_2 \ x_3 \ \dots \ x_N]^T$ . The MLP provides the two coefficients  $A_i$  and  $B_i$  for one harmonic component. For identifying more than one harmonics of the distorted waveform, several MLPs are used as illustrated by Fig. 6. In this structure, each MLP identifies or estimates each desired harmonic waveform parameter. All the MLP networks in this structure use the same input vector  $[x_1 \ x_2 \ x_3 \ \dots \ x_N]^T$  and output the two coefficients of their specific  $i$ -th harmonic component.

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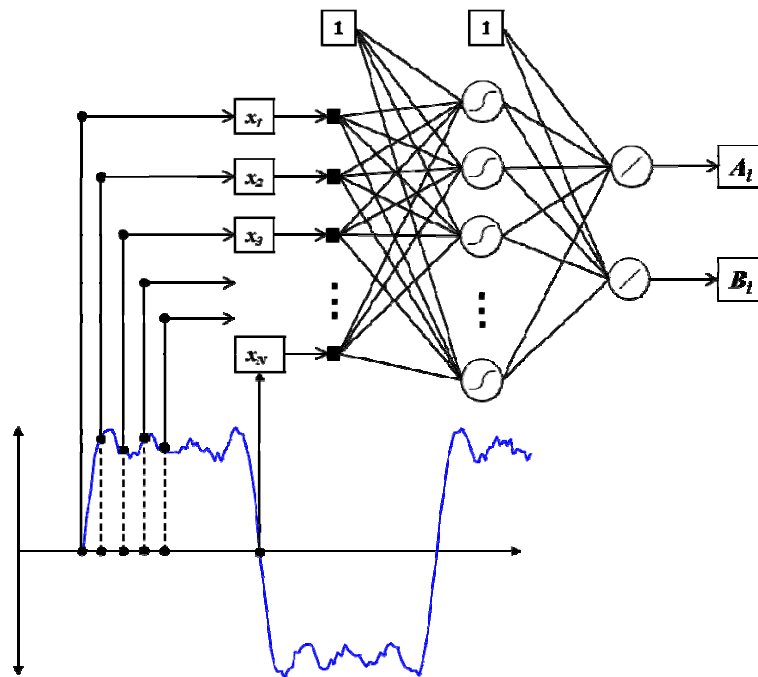


Fig. 5 The proposed MLP for identifying coefficients  $A_i$  and  $B_i$  of a harmonic.

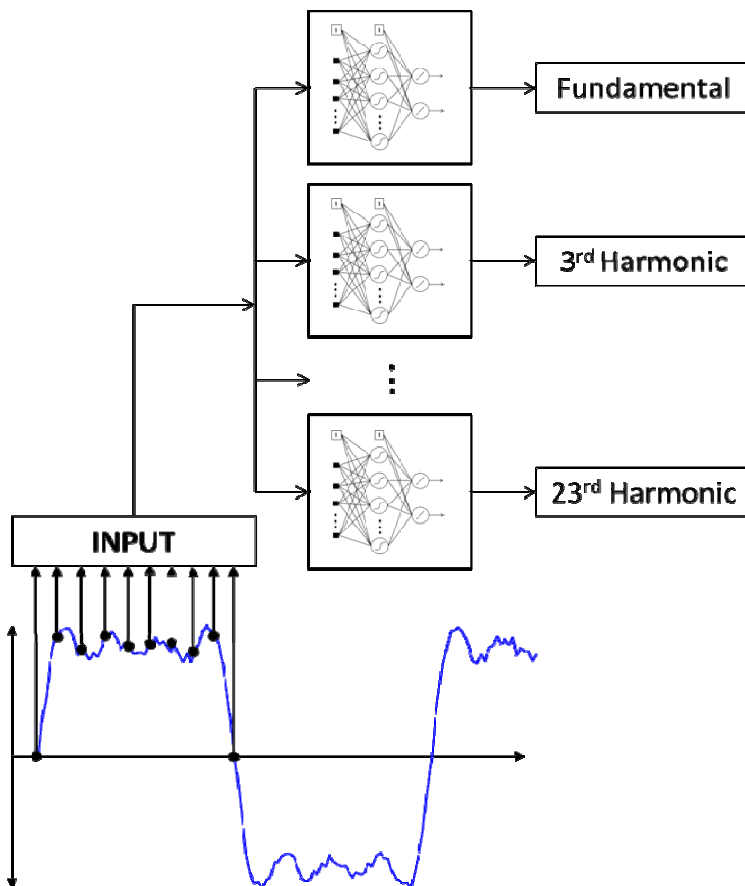


Fig. 6 The proposed structure based on MLP networks for identifying harmonics of ranks 1, 3, 5, 7, 11, 13, 17, 19 and 23.

#### 4. Experimental Results

The performance of the proposed harmonic estimation approach using MLPs is examined through simulation tests. In the following, the performance of the proposed harmonic estimator is compared to the approach presented in Ref. [20]. The two structures are based on MLP networks, they are implemented and tested for performing comparisons of harmonics identification on the same training set of signals. The harmonic estimation approaches have been implemented in the Matlab/Simulink environment.

Two experiments are proposed in order to evaluate the effectiveness of the proposed neural approach for identifying harmonics in distorted signals. In the first experiment, a typical signal with harmonic components of ranks 3, 5 and 7 is used as a reference test. In the second experiment, a real signal is used and it consists in a current measured on a nonlinear load.

For identifying the two coefficients  $A_i$  and  $B_i$  of each  $i$ -th harmonic component of a signal, the first neural structure uses one MLP with two-output. The second neural structure uses two MLPs with one output for identifying the two coefficients of one harmonic component. We compare these two approaches by using approximately the same number of weights per harmonic component to be estimated. Thus, the proposed structure for estimating a harmonic uses one MLP with 51 inputs, 9 hidden neurons and 2 output neurons. The number of weights of this MLP that we need to identify a harmonic component is then  $(51+1) \times 9 + (9+1) \times 2 = 488$  weights. The other structure for estimating a harmonic uses 2 MLPs with 51 inputs, 5 hidden neurons and 1 output neuron. So, the number of weights which are necessary to identify a harmonic component is  $((51+1) \times 5 + 5+1) \times 2 = 532$ . One can note that the number of weights in our approach is lower than for the other approach.

The MLPs of both neural approaches are firstly trained off-line with the same training set before being used online. A conventional BP training algorithm is

used for the learning of the MLPs [26]. The training set is made of data representing normalized distorted waveforms that are randomly generated from a fundamental waveform and from harmonics of ranks 3, 5, 7, 11, 13, 17, 19 and 23. Attention has been given for generating of the data set in order to obtain representative values of the disturbed signals. Fig. 7 shows a training performance example, i.e., for the learning of the 23rd harmonic with an MLP. It should be noticed that this is a very severe case, because the amplitude of the 23rd harmonic component is small compared to the amplitude of the fundamental component (usually less than 4%). With only 12 neurons, an MLP is able to converge quickly even under noisy conditions. The performance index that is used is the MSE (mean squared error).

##### 4.1 Experiment with a Simple Signal

In this first experiment, the test signal used to validate the proposed estimator is a typical waveform composed of a fundamental frequency  $f = 50\text{Hz}$ ,  $\omega = 2\pi f$  and where harmonics of ranks 3, 5 and 7 are added as well as a uniformly distributed noise:

$$s(t) = \sin(\omega t) + \frac{1}{3} \sin(3\omega t) + \frac{1}{5} \sin(5\omega t) + \frac{1}{7} \sin(7\omega t) + \eta(t). \quad (2)$$

This waveform is sampled in discrete time by  $t$  with a sampling  $T_s = 0.0002$  s, and we use 4,000 samples. The measure of noise level of  $\eta(t)$  is the SNR (signal-to-noise ratio) expressed in dB. In this experiment, we choose  $SNR_{dB} = 32$ .

The objective is to identify the 3rd, 5th, and 7th harmonics with the proposed neural approach. Fig. 8 shows the results. In addition, Fig. 9 shows the performance of the other neural approach. These figures show the original distorted signal and the signal reconstructed after the harmonic identification process. The values of the coefficients and the amplitudes of the harmonic components are also plotted. The MSE on reconstructing the signal is 0.064 A and 0.096 A

Table 1 Comparison of performances obtained with the two neural approaches based on MLPs on a simple signal.

Learning strategy	Mean Square Errors—MSE		
	Min	Max	Mean
Proposed neural approach	0.0592	0.0680	0.0635
Other neural approach, i.e., from [20]	0.0896	0.1049	0.0965

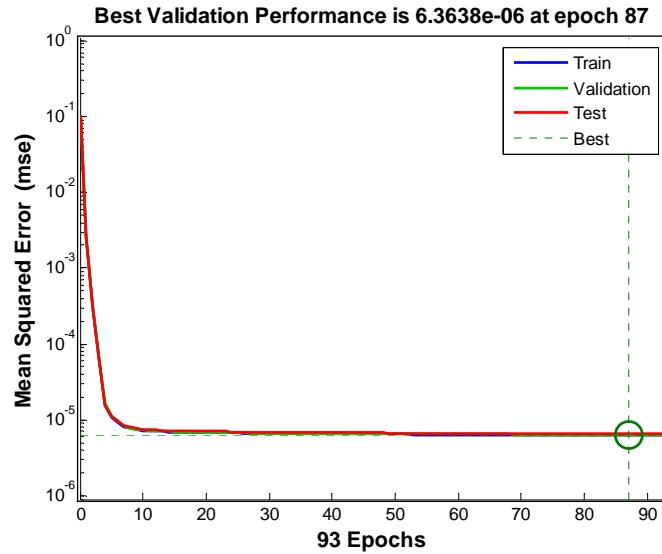


Fig. 7 The proposed structure based on MLP networks for identifying harmonics of ranks 1, 3, 5, 7, 11, 13, 17, 19 and 23.

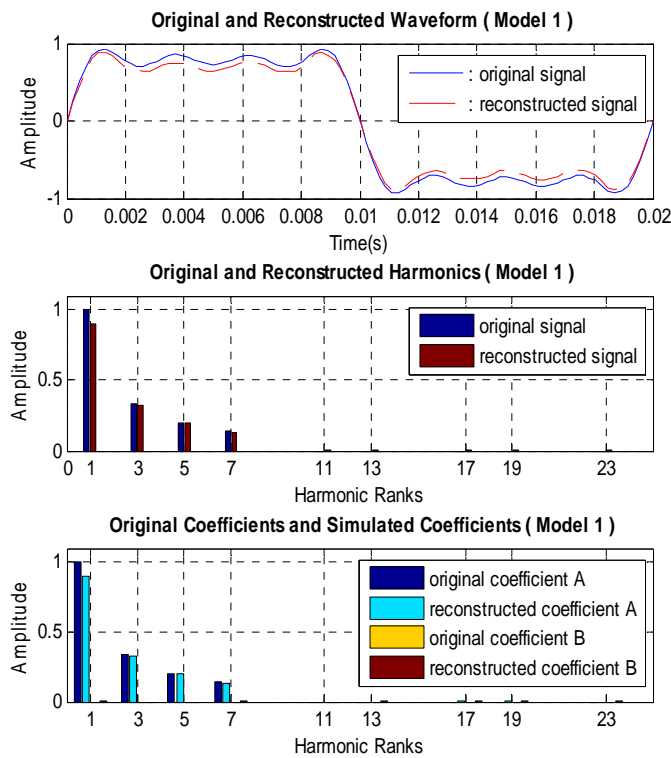


Fig. 8 Harmonic identification of a sine wave with harmonic of ranks 3, 5 and 7 with the proposed neural method.

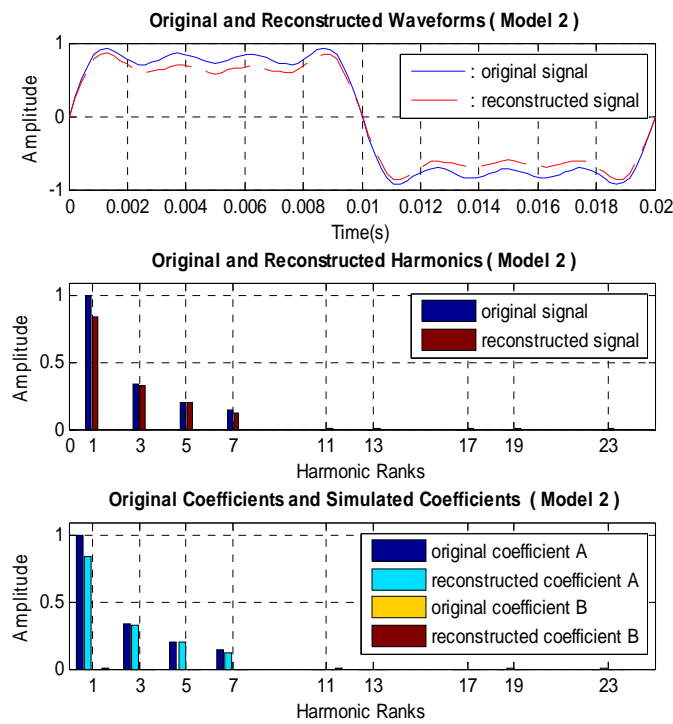


Fig. 9 Harmonic identification of a sine wave with harmonic of ranks 3, 5 and 7 with the other neural method.

Table 2 Comparison of performances obtained with the two neural approaches with a typical real current from a nonlinear load.

Learning strategy	Mean Square Errors—MSE		
	Min	Max	Mean
Model 1	0.4507	0.5025	0.4778
Model 2	0.9805	1.0148	1.0035

respectively with the proposed and to other neural approach. Other numerical comparative values are provided by Table 1. The estimation of the amplitudes and the approximation of the signal are better with the proposed method and with a lower number of weights than the other method. As one can see, the proposed method exhibits generalizing capabilities and is robust against noise.

#### 4.2 Experiment with a Typical Real Current Measured on a Real Nonlinear Load Power Device

In order to evaluate the efficiency of the proposed method in identifying harmonics, we use a typical current that has been measured on a nonlinear load power device characterized by  $f = 50$  Hz, 380 V, 20 A. The proposed neural approach is used to estimate the

amplitudes from the harmonic components found in this current. Fig. 10 illustrates the results obtained with the proposed neural approach, Fig. 11 illustrates the results obtained with the other neural approach and Table 2 compares their numerical performances. Original coefficients  $A_n$  and  $B_n$  for this signal are not available because it is a measured signal but they can be calculated with any frequency analysis method. The error relative to the original signal is calculated to determine the network effectiveness in the harmonic estimation process. After learning and convergence, the MSE is thus 0.455 A with the proposed method and 1.016 A with the other method over one period of the current. This represents respectively less than 2.3% and 5% of the current. Of course, these errors may be related to the number of inputs used by the ANNs, i.e.,

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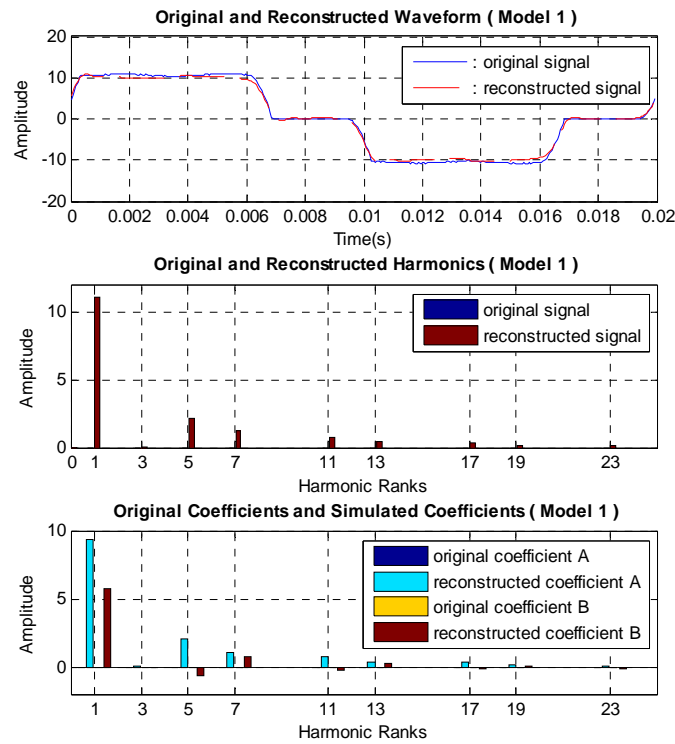


Fig. 10 Experimental results in identifying harmonic components of a current measured from a real nonlinear load with the proposed neural approach.

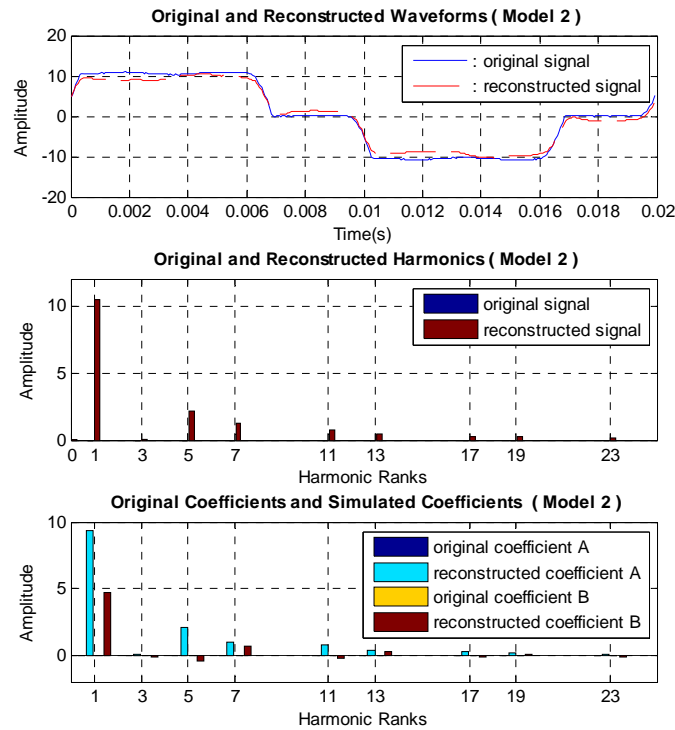


Fig. 11 Experimental results in identifying harmonic components of a current measured from a real nonlinear load with the other neural approach.

are dependent of sampling process.

Additional experiments have been conducted. The proposed neural method has been tested in a single-phase system, considering nonlinear loads popular in industrial applications. The results have shown that the MLP-based method is able to determine the expected harmonic content in half-cycle source voltage. Results on a lot of experiments show that the proposed method has good effectiveness for identifying harmonics of the signals in electrical power systems.

## 5. Conclusion

This paper has presented a new neural architecture based on Multi-Layer Perceptrons (MLPs) for estimating the harmonic contents of electrical power signals. Several MLPs with a reduced number on neurons are used in parallel. An MLP has been dedicated for each individual harmonic component which is supposed to be present in the disturbed signal. As a result, the number of neurons and weights used in the proposed model is less than with other neural techniques. Two examples are presented to illustrate the performance and applicability of the proposed model. The results of the identification approach, compared to other similar methods, are satisfactory. The results showed that the new approach works effectively in estimating each individual harmonic component. Furthermore, this approach is able to identify the harmonic contents with only a half of the fundamental period of the signal even under noisy conditions. This approach can be used to improve power quality issues by being inserted in active power filter schemes creating insensibility against to modeling errors, external disturbing effects and parametric change of the system.

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**Patrice Wira** obtained a Ph.D. degree in automatic control and signal processing in 2002 and the French habilitation to supervise research activities in 2009 from the University of Haute Alsace, Mulhouse, France. Since 2011 he is a Full Professor.

His current research interests are artificial neural networks for modeling and control, signal processing, intelligent control, control of electrical systems, active filtering, current harmonic compensation, and power quality. He is author of over 80 papers published in international journals, conferences and books. Prof. Wira is a Senior Member of IEEE.



**Minh Thien Nguyen** was born in Viet Nam, in 1978. He received a Master of Science degree in computer science at Vietnam National University at Ho Chi Minh City in Vietnam, in 2007.

He is currently working toward to Ph.D. degree in signal processing at the Modeling Intelligence Processing and Systems (MIPS) Laboratory, University of Haut-Alsace in France. His research interests are the Computational Intelligence, Adaptive Filtering, and Power System Applications. Mr. Nguyen is a student member of IEEE.