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Synchronous Reference Frame Based Active Filter Current Reference Generation Using Neural Networks

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***Abstract* – The increased use of nonlinear devices in industry has resulted in direct increase of harmonic distortion in the industrial power system in recent years. The significant harmonics are almost always 5th, 7th, 11th and the 13th with the 5th harmonic being the largest in most instances. Active filter systems have been proposed to mitigate harmonic currents of the industrial loads. The most important requirement for any active filter is the precise detection of the individual harmonic component's amplitude and phase. Fourier transform based techniques provide an excellent method for individual harmonic isolation, but it requires a minimum of two cycles of data for the analysis, does not perform well in the presence of subharmonics which are not integral multiples of the fundamental frequency and most importantly introduces phase shifts. To overcome these difficulties, this paper proposes a Multilayer Perceptron Neural Network trained with back-propagation training algorithm to identify the harmonic characteristics of the nonlinear load. The operation principle of the synchronous-reference-frame-based harmonic isolation is discussed. This proposed method is applied to a thyristor controlled dc drive to obtain the accurate amplitude and phase of the dominant harmonics. This technique can be integrated with any active filter control algorithm for reference generation.**

I. INTRODUCTION

The increased use of modern power electronics technologies by industries has resulted in direct increase of harmonic distortion in the industrial power system in recent years. The improved efficiency and productivity provided by adjustable-speed drives (ASD), uninterruptible power supplies (UPS), etc is offset by the fact that the utility grid is being disturbed by these equipments because of their rectifier front ends. The switching nature of these rectifiers results in a pulsed input current with high harmonic content. Classic utility-side symptoms of harmonics problems are distorted voltage waveforms, blown shunt capacitor fuses, and transformer overheating. Capacitor losses are sensitive to harmonic voltages. Transformer losses are sensitive to harmonic currents.

With the increasing use of power factor correction capacitors installed in the grid for reactive power compensation and the inductance of the lines and transformers, severe *L-C* resonances may be triggered by the harmonic current generated by nonlinear loads. The harmonic current also causes higher losses in the lines and transformers of the utility grid. Harmonic standards, such as the IEEE 519, are strongly recommended by the utilities to alleviate such problems.

Passive *L-C* filters have been the traditionally preferred harmonic filtering solution mainly for their high efficiency, low-cost and simplicity. However, *L-C* filters are susceptible to source-sink resonances [1]. *L-C* filters also attract harmonic current from ambient harmonic-producing loads and background distortion of grid voltages [2]. Filter loading due to background distortion is a key design issue [3]. Their filtering characteristics are affected by component tolerances, and the varying utility system impedances in case of system configuration changes and contingencies. Further, a stiff utility grid poses great difficulties for *L-C* filter design because sharp and precise tuning will be required to sink a significant percentage of the load harmonic current. With all these problems, *L-C* filters may not meet the IEEE 519 standard [4].

Several active filter systems have been proposed to mitigate harmonic current of industrial loads [5]. Pure series and shunt active filters are suitable for small-rating nonlinear loads. Hybrid series and hybrid shunt active filters, which are characterized by a combination of passive *L-C* filters and active filters, are cost effective and practical for large-rated nonlinear loads. Active filtering implemented with pulse width modulated inverters provides good harmonic mitigation. However, a key issue for active filters is to find a control method, which quickly obtains the compensation reference current without errors. The control has two main blocks: the first one generates the control reference signals and the second one carries out the control method. It is, therefore, crucial to be able to recognize the harmonic components in waveform and to reduce them to an acceptable level.

The research literature has identified two groups of spectrum estimation techniques from a data set. The simplest group of approaches uses Fourier based algorithms (FFT and DFT). These algorithms have certain limitations as listed in [6]. The second group of approaches employs more sophisticated techniques like wavelet transforms to track harmonics accurately, but involves complex computational processes [7]. A third trend has emerged over the past couple of years regarding the use of neural network techniques for the control of active filters [8]. The authors of [9] have proposed a system that achieves harmonic isolation at the dominant harmonic frequencies, i.e., at the fifth and seventh harmonics (for six-pulse rectifier front ends), using square-wave inverters.

This paper focuses on the generation of the control reference signal using Multilayer Perceptron Neural Network

(MLPN) trained with backpropagation training algorithm. The synchronous reference frame based harmonic isolation is integrated within the neural network to extract the dominant harmonics. The proposed method is demonstrated on a three phase thyristor controlled DC drive.

II. NEURAL NETWORK IDENTIFIER

Artificial Neural Networks have provided an alternative modelling approach for power system applications. The MLPN [10] is one of the most popular topologies in use today. This network consists of a set of input neurons, output neurons and one or more hidden layers of intermediate neurons. Data flows into the network through the input layer, passes through the hidden layers and finally flows out of the network through the output layer. The network thus has a simple interpretation as a form of input-output model, with network weights as free parameters. The use and training of MLPNs is well understood. Figure 1 shows the block diagram of a three layer MLPN interconnected by weight matrices W and V.

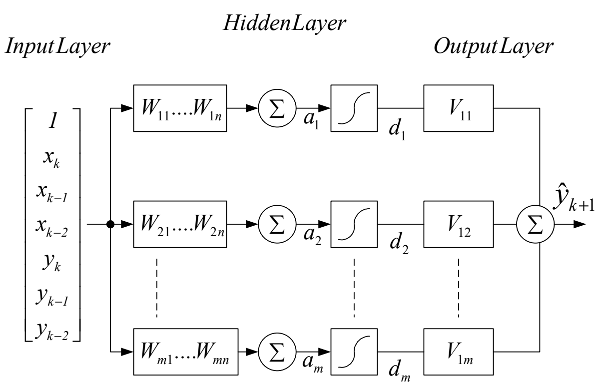

Fig. 1. Structure of a MLPN

The objective of the training is to modify W and V such that the ANN function approximates the plant function and the error e between the desired function output y and the ANN output $\hat{y}$ is minimal. Continual online training (COT) is required whenever the ANN has to track a time varying plant waveform.

The online training cycle has two distinct paths:

- Forward propagation: It is the passing of inputs through the neural network structure to its output.
- Error back-propagation: It is the passing of the output error to the input in order to estimate the individual contribution of each weight in the network to the final output error. The weights are then modified so as to reduce the output error.

The generalized equations are shown below.

A. Forward Propagation

Every input in the input column vector $\underline{x}$ is fed via the corresponding weight in the input weight matrix W to every node in the hidden layer. The activation vector $\underline{a}$ is determined as the sum of its weighted inputs. In vector notation, this is defined as:

$$\underline{a} = W\underline{x} \tag{1}$$

where the input column vector $\underline{x} \in R^n$, the hidden layer activation column vector $\underline{a} \in R^m$, the input weight matrix $W \in R^{m \times n}$, n is the number of inputs to the ANN including the bias and m is the number of neurons in the hidden-layer.

Each of the hidden neuron activations in $\underline{a}$ is then passed through a sigmoid function to determine the hidden-layer decision vector $\underline{d}$.

$$d_i = \frac{1}{1+e^{(-a_i)}},\ i \in \{1,2,....,m\} \tag{2}$$

where the decision column vector $\underline{d} \in R^m$.

The decision vector $\underline{d}$ is then fed to the corresponding weight in the output weight matrix V. The ANN output $\hat{y}$ is computed as:

$$\hat{y} = (V\underline{d})^T \tag{3}$$

For a single output system output weight matrix $V \in R^{1\times m}$ and $\hat{y}$ is a scalar.

B. Error backpropagation

The output error e is calculated as:

$$e = y - \hat{y} \tag{4}$$

The output error is back propagated through the RNN to determine the errors $\underline{e}_d$ and $\underline{e}_a$ in the decision vector $\underline{d}$ and activation vector $\underline{a}$. The decision error vector $\underline{e}_d$ is obtained by back-propagating the output error e through the output weight vector V:

$$\underline{e}_d = V^T e \tag{5}$$

where the decision error vector $\underline{e}_d \in R^m$.

The activation errors e_{ai} are given as a product of the decision errors e_{di} and the derivative of the decisions d_i with respect to the activations a_i:

$$\begin{aligned} e_{ai} &= \left(\frac{d}{da_i} d_i\right) e_{di} \\ &= \left(\frac{d}{da_i}\left(\frac{1}{1+e^{(-a_i)}}\right)\right) e_{di} \\ &= d_i\left(1-d_i\right)e_{di},\ \ i \in \{1,2,....,m\} \end{aligned} \tag{6}$$

The derivative of a sigmoidal function can be expressed in terms of its inputs and outputs and computationally it results in multiplication and addition. The subscript i in (6) indicates element-wise multiplication of the vectors $\underline{d}$, $\underline{1-d}$ and $\underline{e}_d$.

The change in input weights ΔW and output weights ΔV at the k^{th} step are calculated as:

$$\Delta W(k) = \gamma_m \Delta W(k-1) + \gamma_g \underline{e}_a \underline{x}^T$$
$$\Delta V(k) = \gamma_m \Delta V(k-1) + \gamma_g e \underline{d}^T \qquad (7)$$

where $\gamma_{m,}\gamma_g \in [0,1]$ are the momentum and learning gain constants respectively. The last step in the training process is the actual updating of the weights:

$$W(k) = W(k-1) + \Delta W(k)$$
$$V(k) = V(k-1) + \Delta V(k) \qquad (8)$$

III. SYNCHRONOUS REFERENCE FRAME (SRF)

Application of synchronous reference frame (SRF) based harmonic extraction was introduced in [11]. Description of the method as used in this paper is described below. The three phase currents i_a, i_b and i_c are transformed from three phase abc reference frame to two phase $d^s - q^s$ stationary reference frame currents i_d^s and i_q^s using;

$$\begin{bmatrix} i_d^s \\ i_q^s \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & \frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \qquad (9)$$

The currents i_d^s and i_q^s are now transformed to synchronously rotating $d^e - q^e$ reference frame by the unit vectors $\cos\omega_e$ and $\sin\omega_e$ as shown below;

$$\begin{bmatrix} i_q^e \\ i_d^e \end{bmatrix} = \begin{bmatrix} \cos\omega_e & -\sin\omega_e \\ \sin\omega_e & \cos\omega_e \end{bmatrix} \begin{bmatrix} i_q^s \\ i_d^s \end{bmatrix} \qquad (10)$$

The frequency ω_e is derived from the harmonic order that needs to be isolated. It is extremely important to note that the direction of the unit vector rotation has to comply with the sequence of the harmonic extracted. Figure 2 shows the transformation from abc to $d^e - q^e$ reference frame.

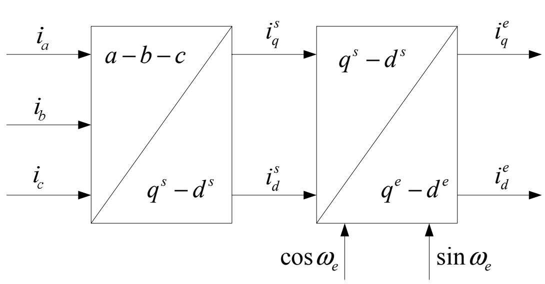

Fig. 2. Block diagram showing abc to $d^e - q^e$ transformation

In the $d^e - q^e$ reference frame, components of ω_e appear as DC quantities and all other harmonics are transformed to non DC quantities. Using a low pass filter, the DC quantity can be accurately extracted. The DC component of the current is now retransformed back to the stationary reference frame using;

$$\begin{bmatrix} i_q^s \\ i_d^s \end{bmatrix} = \begin{bmatrix} \cos\omega_e & \sin\omega_e \\ -\sin\omega_e & \cos\omega_e \end{bmatrix} \begin{bmatrix} i_q^e \\ i_d^e \end{bmatrix} \qquad (11)$$

Finally the components from the stationary reference frame are transformed back to three phase reference frame;

$$\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} i_q^s \\ i_d^s \end{bmatrix} \qquad (12)$$

Since the DC quantity in the $d^e - q^e$ reference frame exactly corresponds to the harmonic frequency of interest, extraction of the DC quantity using the low pass filter ensures exact synthesis of the harmonic current in the abc reference frame. Figure 3 shows the filtering scheme.

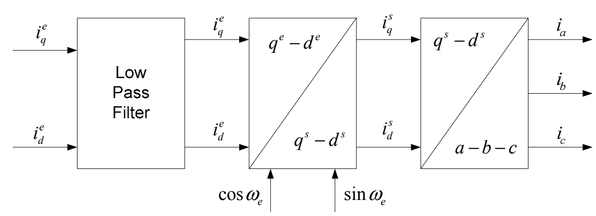

Fig. 3. Block diagram showing $d^e - q^e$ to abc transformation

IV. PROPOSED SCHEME

A one-line diagram of a three-phase supply network having a sinusoidal voltage source v_s, network impedance L_s, R_s and several loads (one of which is nonlinear) connected to a PCC is shown in Fig. 4.

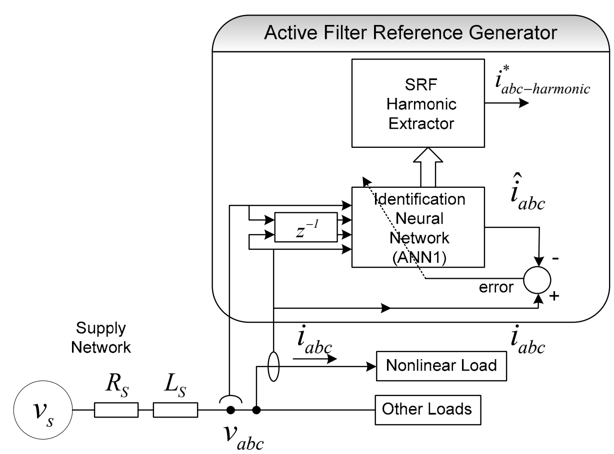

Fig. 4. Proposed scheme for harmonic extraction

The nonlinear load injects distorted line current i_{abc} into the network. A MLPN is trained to identify the nonlinear characteristics of the load. This neural network is called the Identification neural network (ANN1).

A. Identification Neural Network (ANN1)

The proposed method measures the instantaneous values of the three voltages v_{abc} at the PCC, as well as the three line currents i_{abc} at the k^{th} moment in time. The voltages v_{abc} could be line-to-line or line-to-neutral measurements. The neural network is designed to predict one step ahead line current $\hat{i}_{abc}$ as a function of the present and delayed voltage vector values $v_{abc}(k)$, $v_{abc}(k-1)$ and $v_{abc}(k-2)$ as well as present and delayed current vector values $i_{abc}(k)$, $i_{abc}(k-1)$ and $i_{abc}(k-2)$. When the $(k+1)^{th}$ moment arrives (at the next sampling instant), the actual instantaneous values of i_{abc} are compared with the previously predicted values of $\hat{i}_{abc}$, and the difference (or error e) is used to train the ANN1 weights. Initially the weights have random values, but after several sampling steps, the training soon converges and the value of the error e diminishes to an acceptably small value. Proof of this is illustrated by the fact that the waveforms for i_{abc} and $\hat{i}_{abc}$ should practically lie on top of each other. At this point the ANN1 therefore represents the admittance of the nonlinear load. This process is called identifying the load admittance. Since continual online training is used, it will correctly represent the load admittance from moment to moment.

Due to the nature of the sigmoidal transfer function, the outputs of the neurons in the hidden layer are limited to values between 0 and 1. The inputs to the neural networks are therefore scaled and limited to values between ± 1. The scaling of the acquired data is done using software and hence that removes any limitations whatsoever on the data acquisition system and the transducers.

B. SRF Harmonic Extractor

The harmonic extractor is used to isolate the dominant harmonic components from the predicted current $\hat{i}_{abc}$. The three phase reference current $i^{*}_{abc-harmonic}$ can now be used to generate the compensating current at the output of the PWM converter. Many advanced current controller techniques exist for generating the compensating currents, however if the precise harmonic amplitude and phase is not extracted, harmonic compensation may not be successful.

V. RESULTS

The proposed scheme is applied to a simulated DC motor represented by a simplified RL-E model is fed from an inductive three-phase source through a six-pulse thyristor bridge. A pulse generator synchronized on the source voltages provides the trigger pulses for the six thyristors. The converter output current is controlled by a PI current regulator. The scheme is shown Fig. 5.

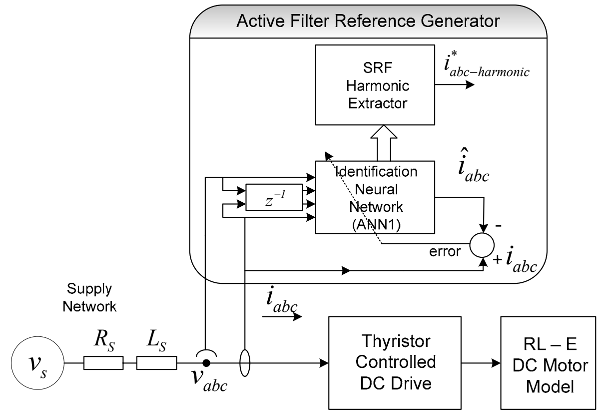

Fig. 5. Harmonic extraction scheme applied to a DC drive

The simulation is run for 20 cycles and data is acquired at the rate of 512 samples per cycle. A 30% step signal is applied to the drive reference current during the 10th cycle to test the dynamic response of the drive's current regulator and the ability of the neural network to identify such changes in current. The input voltage and current data of the load, acquired during these 20 cycles of simulation is used to train the neural network until the training error converges to near zero, and the output of neural network correctly tracks the actual current i_{abc} as shown in Fig. 6. The neural network quickly adapts to the step change, within 1 cycle, and keeps tracking the new current. This is one of the advantages of continual online training.

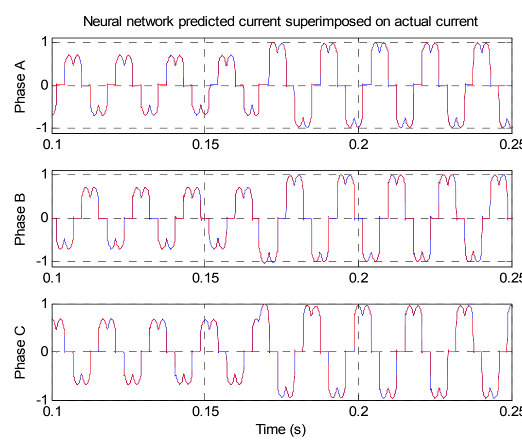

Fig. 6. Training result for the three line currents

The training of the network continues until a desired value of mean squared error (MSE) is reached. The value of the MSE shows the training convergence. Figure 7 shows the MSE in training for all the line currents. For each phase the value is lower than 10^{-5} and that is a sufficiently low value to indicate that the identification neural network is trained and has learned the load characteristics.

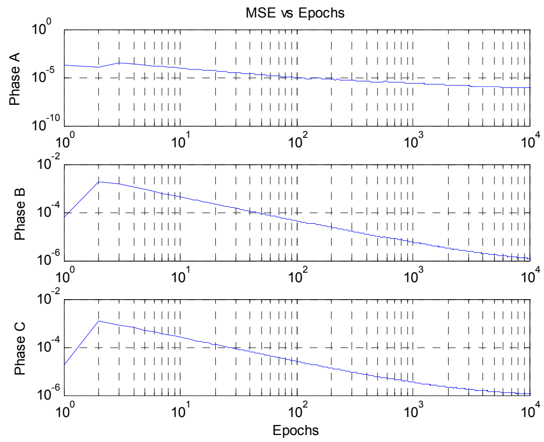

Fig. 7. MSE in current tracking

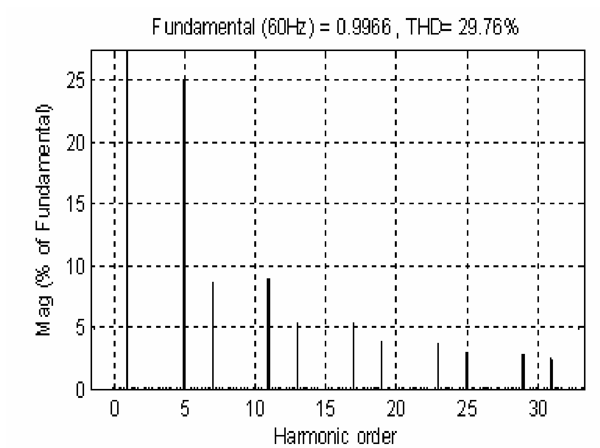

Fig. 8. FFT spectrum of the load current

Figure 8 shows the FFT spectrum of load current obtained using the powergui block of SIMULINK. At this point, the SRF control block in the neural network is activated and the data from the output layer of ANN1 is passed to the SRF block. The performance of the SRF based control method is demonstrated by extracting the 5th and the 7th harmonics and comparing it with the values obtained from Fig. 8.

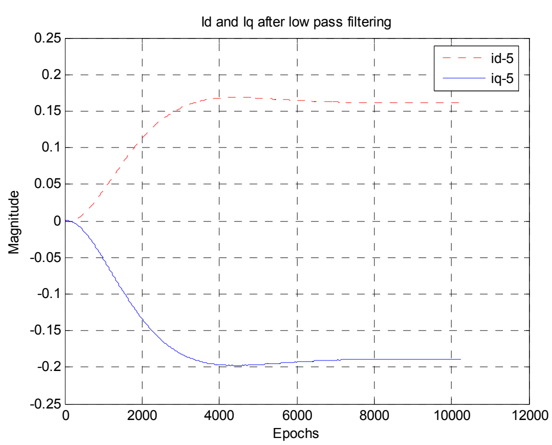

Fig. 9. Fifth harmonic i_d^e and i_q^e after low pass filtering

Figure 10 shows the 5th harmonic current retransformed back in the abc reference frame.

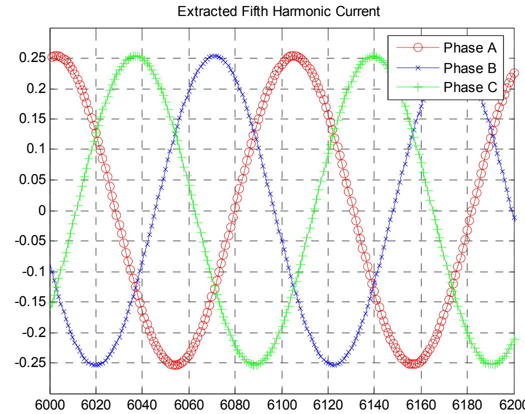

Fig. 10. Fifth harmonic current in the abc reference frame

Extending the method, all the dominant harmonics can be extracted. Figures 11 and 12 shows the result for the 7th harmonic current.

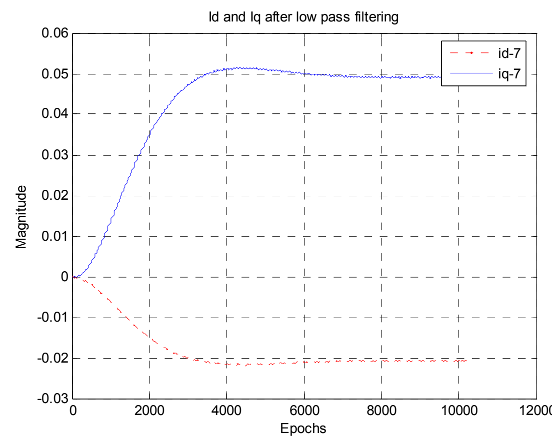

Fig. 11. Seventh harmonic i_d^e and i_q^e after low pass filtering

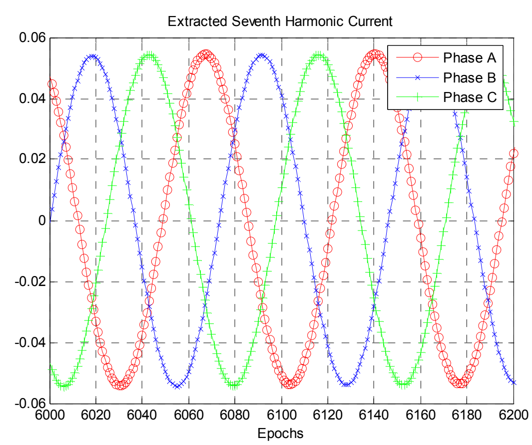

Fig. 12. Seventh harmonic current in the abc reference frame

The harmonic current amplitude and phase values can now be used to generate the reference for the active filter.

Table I provides the magnitude and phase values for the dominant harmonics, namely, 5th, 7th, 11th and 13th. The magnitude values are normalized. Comparison of these results with that from Fig. 8 reveal that the neural network is able to extract the dominant harmonics accurately.

TABLE I
DOMINANT HARMONICS AMPLITUDE AND PHASE EXTRACTION

Harmonic	Phase A	Phase B	Phase C
5th - Mag	0.2596 A	0.2642 A	0.2230 A
5th - Phase	-132.2°	-12.3°	107.8°
7th - Mag	0.0557 A	0.0568 A	0.0477 A
7th - Phase	-110.5°	-9.55°	-129.0°
11th - Mag	0.0843 A	0.0857 A	0.0725 A
11th - Phase	36.26°	156.1°	-83.8°
13th - Mag	0.0404 A	0.0412 A	0.0345 A
13th - Phase	-86.09°	153.5°	33.86°

Details about designing the neural network are available in [12]. Some of the experimental details of the neural network implementation are given below:

- MLP network implemented in MATLAB.
- FFT computation : *powergui* block of SIMULINK
- Number of Neurons in the hidden layer: 25
- Inputs : Voltage and current vector with 2 time delays
- Learning gain: 0.25. Momentum gain not used.
- Sampling frequency for data acquisition: 8 kHz. Power quality instrumentations require ~ 128 samples/cycle.
- Computation time for the MATLAB code to compute the output weights (with 20 cycles of acquired data) run on a 1.8 GHz PC: 3.8 sec

The accuracy of neural network computations can be further increased by increasing the sampling rate and number of neurons. However that puts additional computational demands on the processor and might make the actual hardware implementation more difficult.

VI. CONCLUSION

This paper has demonstrated the ability of MLP neural networks to learn the admittance of a nonlinear load and utilize the trained neural network for generating the compensating current reference for active filters. The proposed method has been successfully applied to a specific three phase load. The advantages of the proposed method are that it can be implemented online without disrupting the operation of any load, only voltages and currents need to be measured. It does not require any special instruments and it does not need to make any assumptions about any quantities, e.g. the impedance of the source.

VII. ACKNOWLEDGMENT

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