Challenges of ANN in Adapting to Abrupt Parameters Variations for Shunt Active Filter

Dehini Rachid [1], Berbaoui Brahim [2]

[1] *Tahri Mohammed University, Béchar, Algeria.* *dehini.rachid@univ-bechar.dz*

[2] *The African University Ahmed Draia,* *berbaoui.brahim@gmail.com*

Abstract: The purpose of the shunt active power filter (SAPF) goes beyond simply improving power factor; it also aims to mitigate unwanted harmonic currents generated by nonlinear loads. This research introduces a SAPF equipped with an identification and control method utilizing artificial neural networks (ANN). Various techniques are employed for harmonic identification, including traditional p-q theory and the relatively recent approach of artificial neural networks. Achieving satisfactory identification and control characteristics is challenging when dealing with the nonlinearity of the system, particularly in situations involving rapid nonlinear load fluctuations. This study represents a systematic effort to address this challenge by enhancing the SAPF with a method for harmonics identification and DC link voltage control based on ANN. This approach is tested on the SAPF under conditions of fast, nonlinear load variations. The study includes both computer simulations and experimental results, which provide evidence of the viability and effectiveness of the proposed active power filter.

Keywords: Shunt active power filter, power factor, harmonic currents, nonlinear loads.

1. INTRODUCTION

In recent years, the extensive use of power electronic devices and nonlinear loads, which employ switching components like high-power diode/thyristor rectifiers, arc furnaces, cyclo-converters, and variable speed drives, has led to a degradation of signal quality in transmission and distribution systems. Consequently, the issue of harmonic pollution and its mitigation has become highly significant. These harmonics disrupt the performance of delicate electronic equipment and result in unwanted power losses. Therefore, it is strongly advisable to address and resolve this problem [1], [2].

To mitigate these unwanted harmonics, conventional methods have relied on the use of power passive filters (PPF), which are known for their simplicity and cost-effectiveness. Nevertheless, they come with significant disadvantages, including their bulky physical size, the need for precise tuning, and the potential for resonance issues. These drawbacks can reduce the flexibility and overall reliability of the filtering devices.

The drawbacks associated with power passive filters (PPF), combined with the rapid advancements in semiconductor device technology, which have enabled the development of high-speed, high-power switching devices [3], have directed the focus of researchers toward shunt active power filters (SAPF). As a result, SAPF has gained increasing attention and has been progressively acknowledged as a viable solution to issues arising from nonlinear loads [4-6].

In general, the effectiveness of SAPF hinges on three primary design criteria: (i) the design of the power inverter, (ii) the selection of controller types, and (iii) the methods employed to determine the reference current. This study primarily emphasizes the second and third criteria.

To assess the harmonic and reactive components of the load current, the generation of a reference source current is a necessary step [7]. Consequently, the reference filter current can be derived by subtracting it from the total load current, as shown in "Fig. 1". To optimize filter performance, it's crucial to generate the reference source current accurately [6]. Various methods have been introduced in the literature for this purpose, including the pq-theory, dq-transformation [7], multiplication with sine functions, and Fourier transform [8].
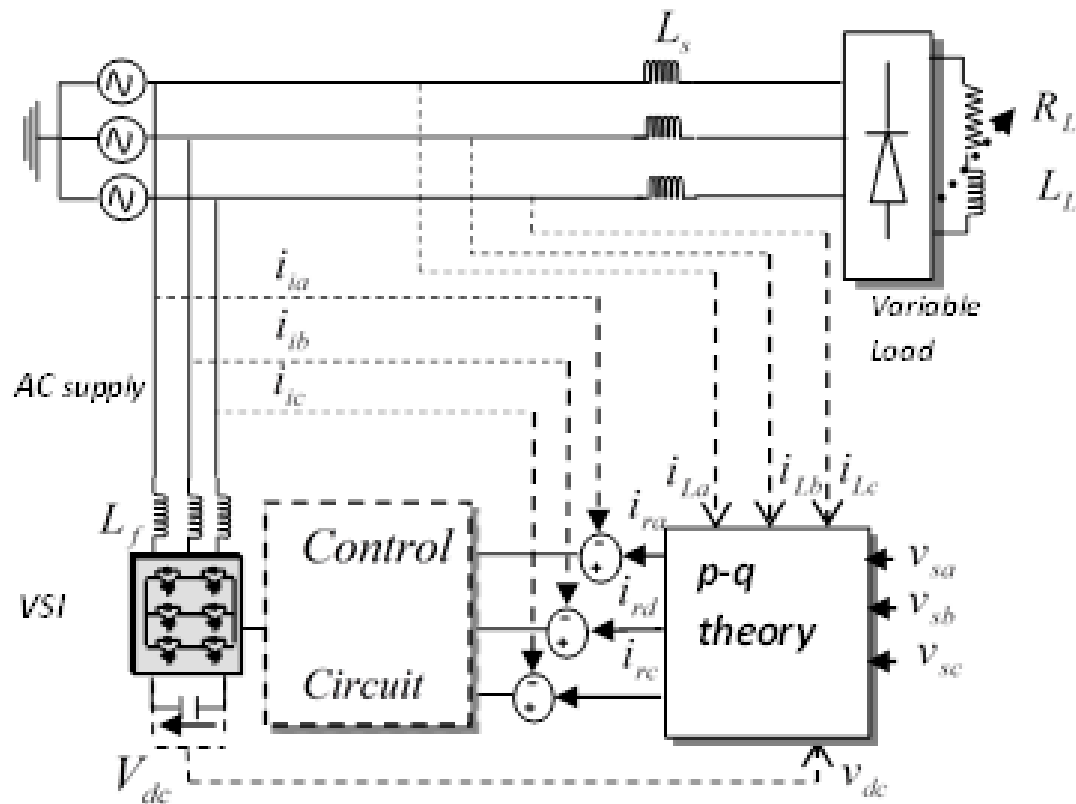
Fig 1. Diagram illustrating the layout or configuration of a shunt Active Power Filter (APF).

Lately, there has been a growing trend in utilizing artificial intelligence methods to enhance the speed of detecting harmonic currents. Over the past decade, there has been a significant surge in interest surrounding Artificial Neural Networks (ANNs), known for their capacity to learn, rapid recognition, and straightforward architecture. ANNs have found applications in various areas within power electronics, including machinery [3] and filtering devices [9], where their effectiveness has been evident. The outcomes achieved with ANNs often outperform those of conventional methods. This is because ANNs can optimize their weights and biases concurrently through an online training process, enabling them to adapt effectively to various systems.

This research paper introduces a detection technique employing artificial neural networks (ANN) capable of serving two purposes: detecting harmonic currents in distorted waveforms and controlling DC link voltage. This method offers the ability to efficiently derive the reference current for each phase. One noteworthy feature of this method is its adaptability, as it allows for the adjustment of the learning rate across a broad range without significantly affecting performance. This is achieved through a straightforward and well-supported theoretical framework [9].

The research conducted by the authors [10] has demonstrated that the artificial neural network (ANN) method can operate optimally across a wide range of operational conditions and disturbances, providing effective results under constant load. However, in real-world scenarios, nonlinear loads are not constant and can vary unpredictably. Under rapidly changing conditions, conventional ANN-based control for SAPF may not yield satisfactory performance, resulting in a degradation of system performance. To address these challenges, a novel ANN has been developed to accommodate both stationary and variable load states, leading to an enhancement in the overall performance of SAPF. The performance of this newly designed ANN is assessed through simulations and compared to previous research findings.

2. GENERATION OF REFERENCE SOURCE CURRENT

The fundamental idea behind the "instantaneous reactive power theory" method, also known as the p-q theory, primarily involves transforming variables from the a, b, c reference frame of instantaneous power, voltage, and current signals into another reference frame [11]. The instantaneous values of voltages and currents in these new coordinates can be derived using the following equations:

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = [A] \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix}, \quad \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = [A] \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix}$$

(1)

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = [A] \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix}, \quad \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = [A] \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix}$$

(2)

Here, A represents the transformation matrix, which is defined as:

$$[A] = \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix}$$

(3)

This transformation remains valid under the condition that the product of matrix A and its transpose ($v_a(t) + v_b(t) + v_c(t) = 0$) is satisfied. Additionally, for this transformation to be accurate, it requires that the voltages are both balanced and sinusoidal. The instantaneous active and reactive powers in the new reference frame, denoted as $\alpha - \beta$, can be determined using the following expressions:

$$p(t) = v_\alpha(t) i_\alpha(t) + v_\beta(t) i_\beta(t)$$

(4)

$$q(t) = v_\alpha(t) i_\beta(t) - v_\beta(t) i_\alpha(t)$$

(5)

The values of p and q can be described based on the equations (3) and (4), as a combination of both the DC components and the AC components. In other words:

$$p = \overline{p} + \tilde{p}$$

(6)

$$q = \overline{q} + \tilde{q}$$

(7)

Here's a breakdown of the terms:

$\overline{p}$: represents the DC component of the instantaneous power, denoted as p. It is associated with the conventional fundamental active current.

$\tilde{p}$: signifies the AC component of the instantaneous power p. It lacks an average value and is linked to the harmonic currents stemming from the AC component of the instantaneous real power.

$\overline{q}$: stands for the DC component of the imaginary instantaneous power, known as q. It relates to the reactive power generated by the fundamental components of voltages and currents.

$\tilde{q}$: represents the AC component of the instantaneous imaginary power q. It is linked to the harmonic currents arising from the AC component of the instantaneous reactive power.

To offset the reactive power and the harmonic currents produced by nonlinear loads, the reference signal for the shunt active power filter needs to encompass the values of $\tilde{p}$ and $\tilde{q}$. In this scenario, the reference currents needed for the SAPF are determined using the following expression:

$$\begin{bmatrix} i^*_{c\alpha} \\ i^*_{c\beta} \end{bmatrix} = \frac{1}{v^2_{\alpha}+v^2_{\beta}} \begin{bmatrix} v_{\alpha} & v_{\beta} \\ v_{\beta} & -v_{\alpha} \end{bmatrix} \begin{bmatrix} \tilde{P}_L \\ \tilde{q}_L \end{bmatrix}$$

(7)

The ultimate compensating current components in the a, b, c reference frame are as follows:

$$\begin{bmatrix} i^*_{ca} \\ i^*_{cb} \\ i^*_{cc} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} i^*_{c\alpha} \\ i^*_{c\beta} \end{bmatrix}$$

(9)

3. NEURAL NETWORKS FOR CONTROLLING REFERENCE SOURCE CURRENT AND DC VOLTAGE

Today, one of the widely adopted topologies is the Multilayer Feed Forward Neural Network (MLFFN) [11]. This network is composed of an array of output neurons and one or more intermediate neurons, referred to as hidden layers. The flow of information within the network starts at the input layer, traverses through the hidden layers, and ultimately exits through the output layer. A three-layer MLFFN is interconnected through weight matrices denoted as W and bias vectors represented by b, which serve as the free parameters. You can find the block diagram illustrating this configuration in "Fig. 2" and "Fig. 3."

To adjust the weight matrix W and bias vector b, the Artificial Neural Network (ANN) undergoes a training process. During this process, the ANN seeks to approximate its function to match the system function, minimizing the disparity between the actual output, denoted as y, and the reference function. Each individual input within the input column vector X is assigned a specific weight from the weight matrix W. The collective sum of these weighted inputs, in addition to the bias, constitutes the input to the transfer function F.
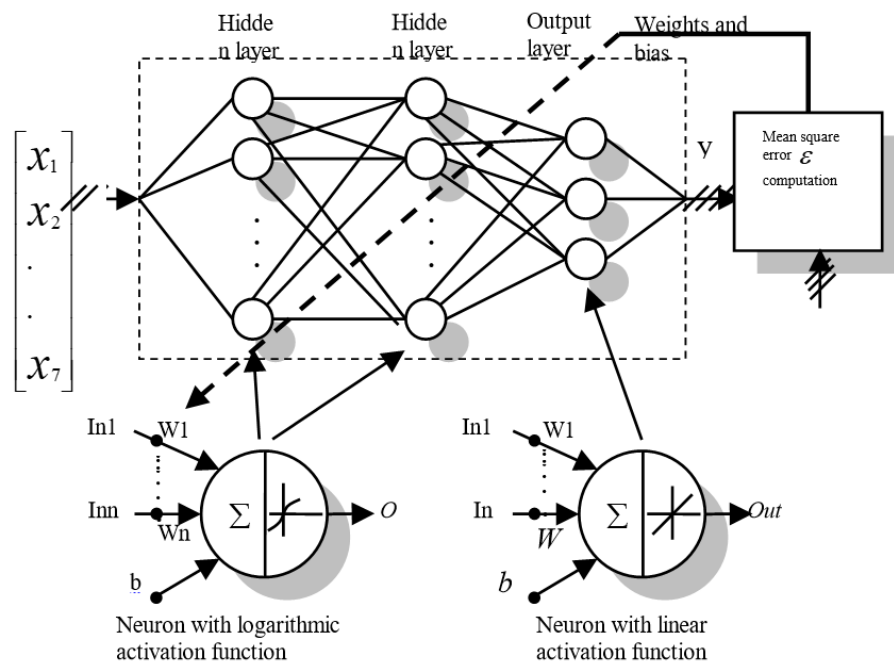

Fig. 2 "Modeling a Controller Method using Neural Networks"

The activation vector "a" is determined as:

$$a = \sum (w \cdot x + b)$$

(10)

Neurons have the flexibility to employ a variety of differentiable transfer functions, denoted as F, to produce their outputs. In this specific instance, the tan-sigmoid transfer function, referred to as the tansig function, is applied in both the input layer and the hidden layer.

$$\tan\sin g(a) = \frac{2}{1+e^{-2a}} - 1$$

(11)

Conversely, the output layer employs the linear transfer function known as purelin.
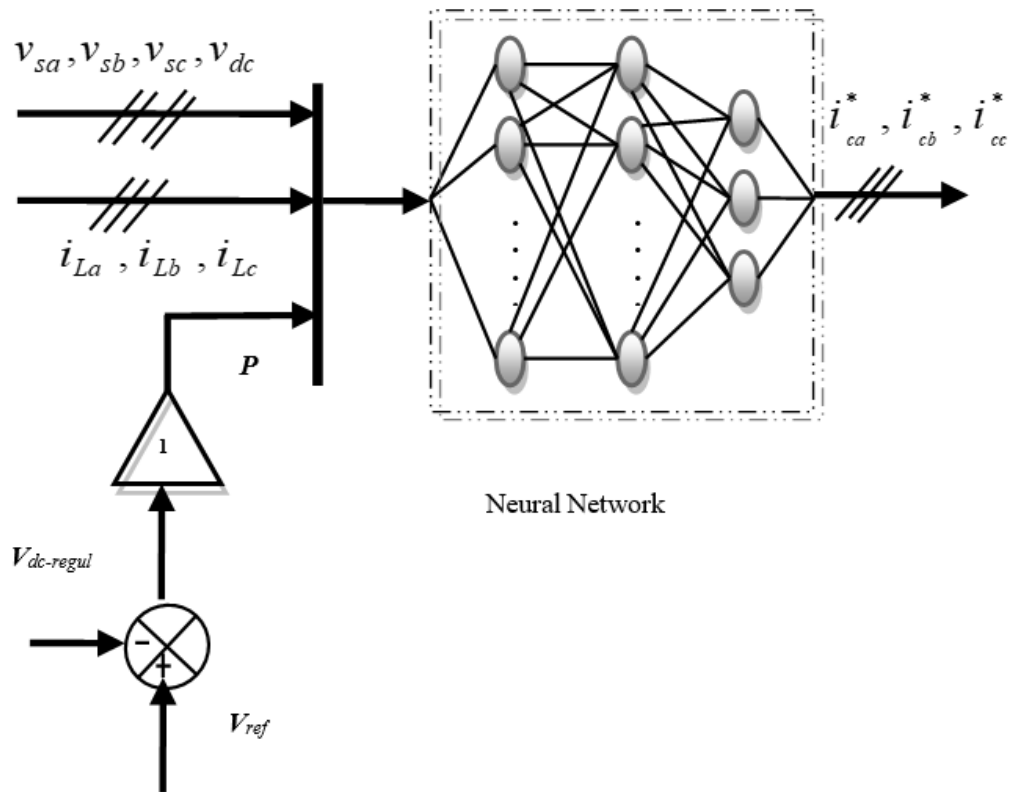
$Purelin\ (a) = a$ (12)

Fig. 3 "Model of an Adaptive Artificial Neural Network (ANN) Controller Test System"

In this study, the least mean square error (LMS) algorithm is employed to oversee the training process. This learning algorithm is guided by a defined set of desired network behaviors:

$$\{x_1, y_1\}, \{x_2, y_2\}, \ldots \{x_n, y_n\}$$

(13)

Here, an input is presented to the network, and there's a corresponding target output. For each input fed into the network, a comparison is made between the network's output and the target output. The error is determined by measuring the difference between the target output and the network's actual output. The mean value of the sum of these errors is then computed as:

$$\varepsilon = \frac{1}{n}\sum_{k=1}^{n} e(k)^2$$

(14)

$$\varepsilon = \frac{1}{n}\sum_{k=1}^{n} (y(k) - y'(k))^2$$

(15)

Where: $y'(k)$ is the network output, $y(k)$ is the target output.

The modification of the weight (W) and bias (b) in the ANN primarily relies on two factors: firstly, the calculation of the mean square error (LMS), and secondly, the application of the "Levenberg-Marquardt backpropagation" algorithm

[11]. For the purpose of identification and filtering, each phase is taken out of the electrical network, and the load current is decomposed into a Fourier series, as outlined below:

$$i_c(t) = i_{lf}(t) + i_{lh}(t) \tag{16}$$

In this expression $i_{lf}(t)$ represents the fundamental current and $i_{lh}(t)$ represents the harmonic current as:

$$i_{lf}(t) = I_{11}\cos(\omega t - \alpha) + I_{12}\sin(\omega t - \alpha) \tag{17}$$

$$i_{lh}(t) = \sum_{n=2}^{49} I_{n1}\cos(n\omega t - \alpha) + I_{n2}\sin(n\omega t - \alpha) \tag{18}$$

Here, ω represents the fundamental frequency of the electrical network, and α is an arbitrary angle, which can be set to zero if needed. I_{11} and I_{12} correspond to the amplitudes related to the cosine and sine components of the fundamental current, while I_{n1} and I_{n2} pertain to the cosine and sine components of the harmonic current.

The outputs produced by this network ($i_{ca}^*, i_{cb}^*, i_{cc}^*$) consist of three components, representing the cosine and sine terms derived from the Fourier series decomposition.

$$i_{ca}^* = i_f(t) + \sum_{n=2}^{49} I_{n1}\cos(n\omega t - \alpha) + I_{n2}\sin(n\omega t - \alpha) \tag{19}$$

In this context, "$i_f(t)$" signifies the fundamental current responsible for charging the capacitor.

4. RESULTS FROM SIMULATION

To evaluate the effectiveness of the suggested detection and control approach, simulations were conducted. The system model was implemented within the Matlab/Simulink environment. The Shunt Active Power Filter (SAPF) was designed to mitigate harmonics stemming from nonlinear loads when the network has a medium proximity to the load (Ssc/SL = 500). The parameters of the system model are detailed in Table I.

TABLE I. Units for Magnetic Properties

Parameters	
Supply phase voltage U	220 V
Supply frequency fs	50 Hz
Filter inductor Lf	0.7 mH
Dc link capacitor Cf	0.768474 mF
Vdc	857V
Smoothing inductor Lsmooth	70 µH

A three-phase diode rectifier, coupled with an RL load, was utilized as the source of harmonic generation. Initially, the load had a resistance of 10/3 Ω and an inductance of 60 mH, resulting in a load apparent power of SL=81 VA. The Artificial Neural Network (ANN) shown in "Fig. 3" featured seven inputs ($v_{sa}, v_{sb}, v_{sc}, P_f, i_{sa}, i_{sb}, i_{sc}$) and three outputs ($i_{ca}^*, i_{cb}^*, i_{cc}^*$). This ANN consisted of two hidden layers, each containing 12 neurons, and an output layer with 3 neurons. The activation function employed was the hyperbolic tangent sigmoid for the two hidden layers, and a linear activation function for the output layer neurons.

The load power was modified in a sequence: initially reduced to 25% at 0.2, raised to 25% at 0.4, increased again to 25% at 0.6, and then decreased to 25% at 0.8. This load variation is illustrated in "Fig. 4" and "Fig. 5". Subsequently, the total harmonic distortion was evaluated at 2.5 kHz for each of these scenarios.
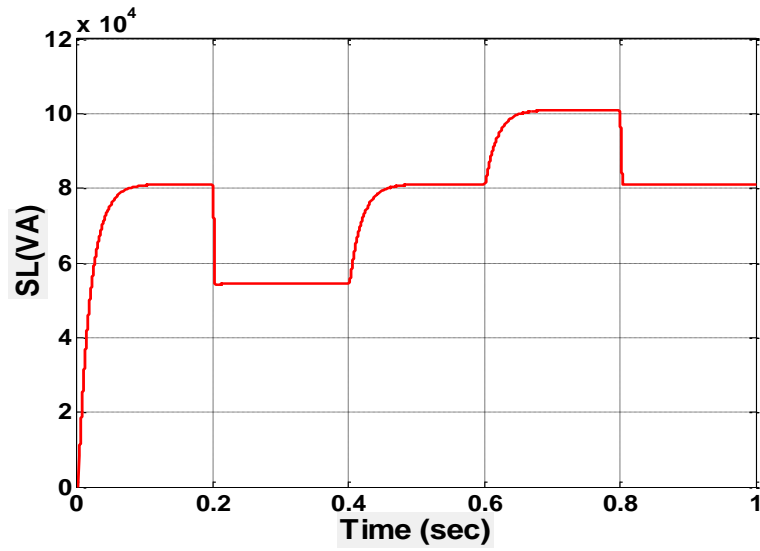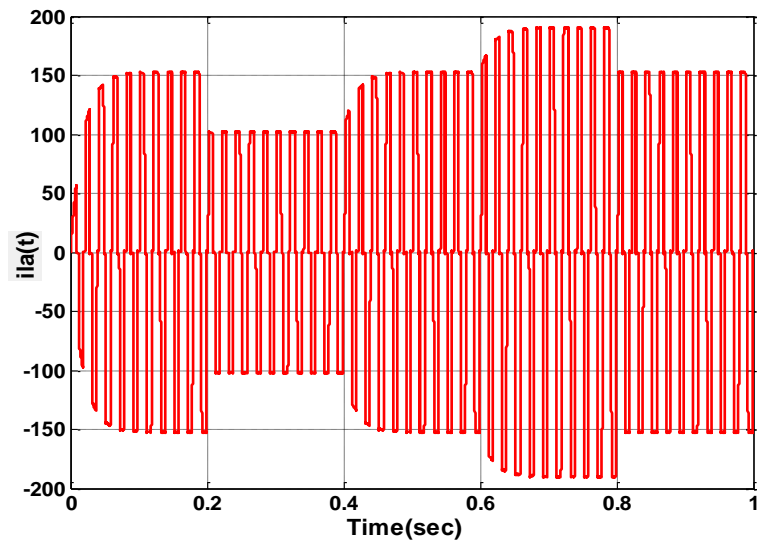
Fig. 4 Apparent power of the load (SL)

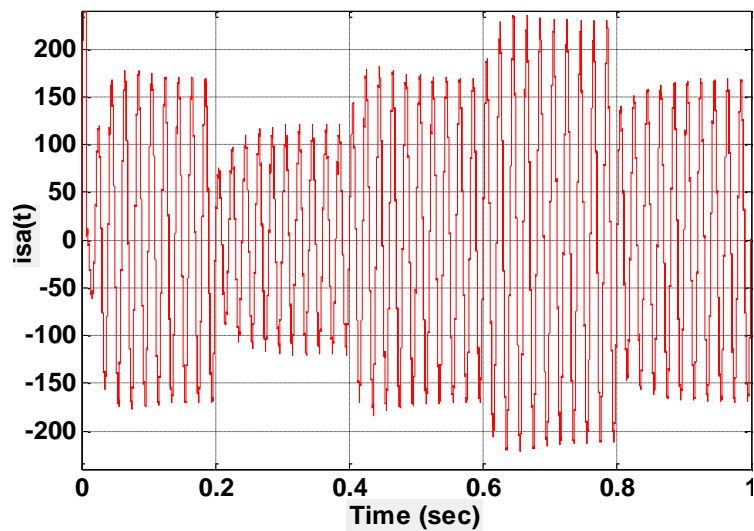**Fig. 5** Current waveforms for phase A of the load

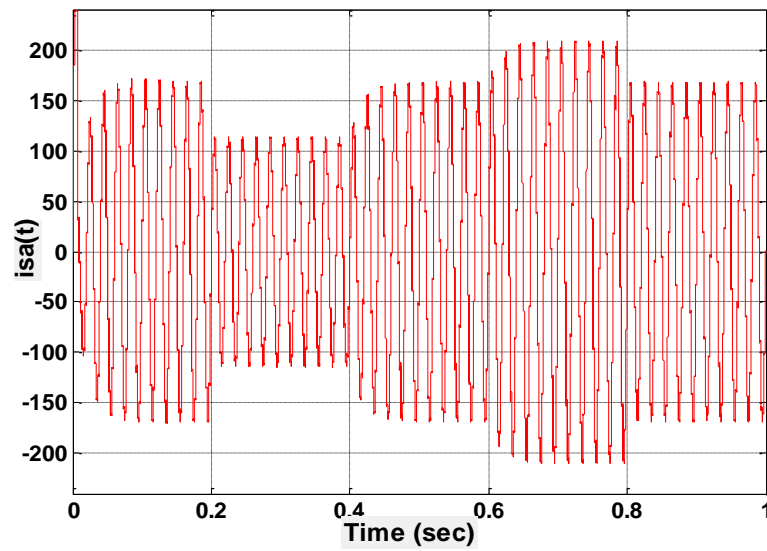**Fig. 6** Current phase A of the supply based on the p-q theory.

Fig. 7 Current waveforms for phase A of the supply using conventional Artificial Neural Network (ANN) control.
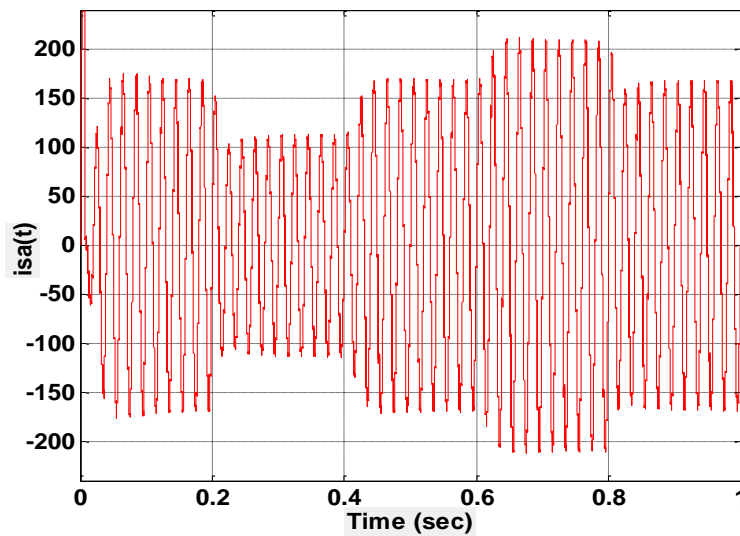

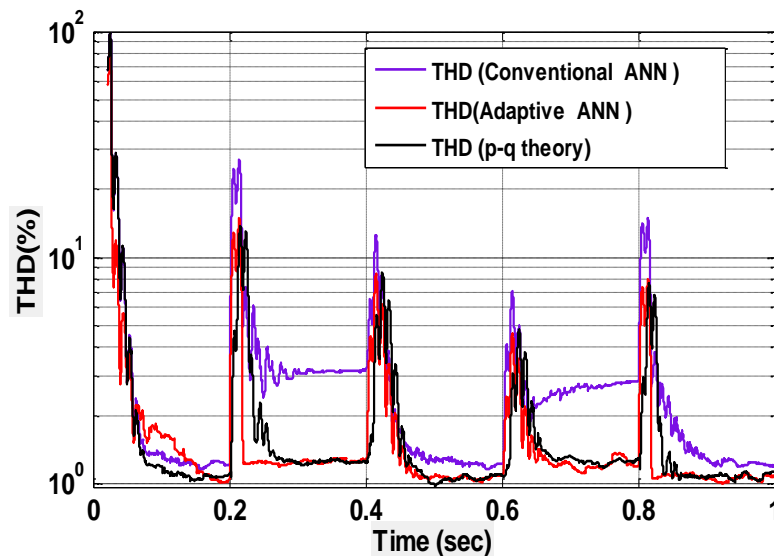**Fig. 8** Current waveforms for phase A of the supply with adaptive Artificial Neural Network (ANN) control.

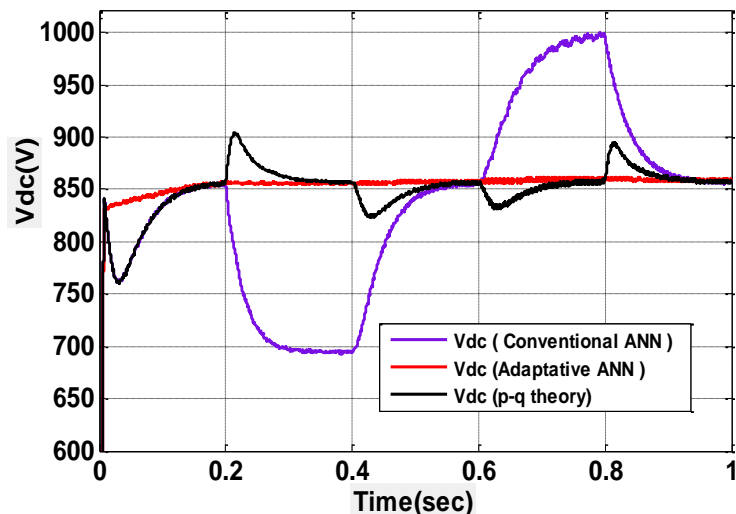**Fig. 9** Variations in the Total Harmonic Distortion (THD) for the three techniques.

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Fig. 10 The DC-link voltage across the three methods while undergoing a load change.

5. DISCUSSION OF THE OBTAINED OUTCOMES.

The simulation involved the use of three distinct methods for load identification and Shunt Active Power Filter (SAPF) control. The simulation results indicate that an increase in load current can lead to excessive harmonic content in the supply current, and the conventional ANN method may struggle to respond adequately to load variations, as observed in "Fig. 7" and "Fig. 9."

The filtering outcomes are illustrated in "Fig. 6" and "Fig. 9." These figures show that deformations have been significantly reduced, and harmonics have been mitigated effectively through the use of adaptive ANN. The Total Harmonic Distortion (THD) calculated up to 2.5 kHz consistently remains lower than the THD observed in the case of conventional ANN and the (p-q theory-PI controller) throughout the load variation.

The quantitative analysis, as shown in "Fig. 9," validates the findings from the qualitative assessment. Across the four performance indices, it is evident that the adaptive ANN method outperforms the other two approaches. This trend is further underscored in "Fig. 4," where the conventional ANN controller succeeds in reducing Total Harmonic Distortion (THD) when load conditions vary, yet it struggles to maintain a consistent voltage level across the capacitor terminals, as depicted in "Fig. 10."

6. CONCLUSION

This paper builds upon prior research and addresses issues encountered with the performance of Shunt Active Power Filters (SAPF) in the presence of sudden load variations. The conventional ANN method falls short in maintaining a consistent average voltage across the capacitor terminals, which is essential for ensuring a smooth power transfer to the inverter. To overcome this challenge, a novel approach based on intelligent neural techniques has been developed and proposed. The performance of this innovative adaptive ANN was assessed through simulation studies conducted in Matlab and compared against conventional ANN and the (p-q theory-PI controller). The results obtained confirm that the newly proposed approach, along with the (p-q theory-PI controller), effectively fulfills the objectives related to harmonic current identification. However, the distinctive advantage of the adaptive ANN lies in its rapid regulation of the capacitor DC voltage in the SAPF during load variations, achieved without the need for a separate controller.

7. REFERENCES

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