Indonesian Journal of Electrical Engineering and Computer Science
Vol. 37, No. 1, January 2025, pp. 35~47
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v37.i1.pp35-47

ADALINE-based synchronous detection for enhanced shunt APF performance

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Article Info

Article history:

Received Apr 8, 2024
Revised Sep 6, 2024
Accepted Sep 29, 2024

Keywords:

ADALINE neural network
Non-linear load
Shunt active power filter
Synchronous detection method
Total harmonic distortion

ABSTRACT

Power quality issues caused by current harmonics from nonlinear and unbalanced loads are a growing concern. This paper presents a novel control strategy for four-wire shunt active power filters (SAPF) that surpasses existing conventional methods in mitigating harmonics and power factor correction. The strategy employs an improved synchronous detection method (SDM) enhanced by an adaptive linear neural network (ADALINE) trained using the least mean square (LMS) algorithm. This approach accurately estimates harmonic frequencies, enabling the SAPF to generate precise compensation currents. The effectiveness of the proposed method is validated through MATLAB-Simulink simulations under balanced supply conditions, encompassing diverse load scenarios. These simulation results are compared with those obtained using instantaneous power theory (IPT). They demonstrate the ability of the proposed method to achieve excellent harmonic identification and elimination, to comply with IEEE 519 harmonic limits, to ensure sinusoidal and balanced line currents, and to compensate for reactive power and neutral current. Furthermore, its simple architecture and noise robustness make it a promising solution for enhancing power quality.

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1. INTRODUCTION

Modern power systems deliver alternating sinusoidal voltage and current at 50 Hz or 60 Hz. However, complex and dynamic electrical networks are subject to disturbances during electricity transmission that distort and imbalance these waves. These disturbances often result from the loads connected to the grid, including the increasing introduction of power electronic components in industrial, commercial, and domestic devices. While these components are advantageous for their flexibility and optimization of performance, they induce nonlinear behavior, generating harmonic currents that pollute the grid. Odd harmonics, especially the 3rd, 5th, and 7th-order harmonics, are especially harmful as they represent a significant portion of disturbances, causing overheating, increased energy losses, and interference [1]. Thus, it is crucial to detect and compensate for these harmonics to maintain optimal power quality.

To mitigate the adverse effects of harmonics, various filtering techniques have been developed. Passive filters, composed of simple elements such as resistors, inductors, and capacitors, are a simple yet inflexible solution to load variations [2]. Active power filters (APFs), on the other hand, offer a more efficient and reliable solution. These filters inject compensating currents at the point of common coupling (PCC) to neutralize unwanted harmonics. Among APFs, four-leg shunt APFs stand out for their ability to handle four-wire systems (three-phase with neutral), where nonlinear and unbalanced loads are common [3], [4]. The control system of APFs operates in three key stages: harmonic identification algorithms, intermediate circuit voltage regulation, and current control algorithms.

Accurate harmonic identification is crucial for the effective operation of APFs. Among the most important conventional techniques are the synchronous reference frame (SRF) method and the instantaneous power (PQ) theory [5]-[7]. Although each of these techniques has unique advantages, they are both limited by their computational complexity and sensitivity to noise [8]. Recent advancements in artificial intelligence offer new perspectives for harmonic identification. Artificial neural networks, particularly adaptive linear neuron (ADALINE), provide a solution well-suited to this task. Thanks to its LMS learning algorithm, ADALINE adapts in real time to variations in the electrical network, providing accurate and rapid estimates of reference currents. Its simplicity and effectiveness make it a preferred tool for analyzing three-phase electrical systems [9], [10]. Numerous studies confirm the superiority of ADALINE over traditional methods, especially for extracting fundamental and harmonic components.

Early implementations of ADALINE in single-phase systems demonstrated its effectiveness under ideal voltage conditions and steady-state operation [11]. Subsequent studies, such as the fundamental active current (FAC)-ADALINE, extended its application to dynamic conditions [12]. Further research expanded the use of ADALINE to three-phase, three-wire systems [13], [14]. The single-phase ADALINE technique was adapted to three-phase systems by applying it to each phase individually, thereby simplifying design through its modular structure. These ADALINE-based approaches have been validated through simulations and experiments under various conditions, including sinusoidal sources, balanced loads, and dynamic states [15], [16]. However, the increasing complexity of wide-band ADALINE has motivated the exploration of selective compensation strategies. By targeting the most problematic harmonics (5^{th} and 7^{th}), it is possible to significantly reduce filter size, improve dynamics, and optimize cost [17], [18].

To enhance the performance of ADALINE-based harmonic extraction, synchronizers such as zero-crossing detectors (ZCDs) and phase-locked loops (PLLs) are often required [19], [20]. These components align the reference signal phase with that of the electrical network, ensuring accurate fundamental current estimation. However, integrating ZCDs and PLLs can complicate system structure. An innovative alternative is the unified ADALINE technique, which uses double ADALINE structures to extract fundamental voltage and current signals, thus eliminating the need for additional synchronizers [21]. Although this approach is effective under ideal conditions, it encounters difficulties when source voltages are distorted or unbalanced. To address this, techniques such as highly selective filters (HSF) and self-tuning filters (STFs) have been developed [22], [23]. The ADALINE technique based on HSF or STFs has shown promising results under various distortion and imbalance conditions, improving the robustness and accuracy of harmonic extraction.

Recent advancements have focused on modifying the ADALINE learning algorithm to enhance its performance. An improved variant of the latest, the variable step size leaky least mean square (VSSLMS) algorithm, was introduced in [24]. This algorithm dynamically adjusts the step size, particularly during convergence periods. However, challenges remain in the presence of distortions or voltage imbalances. To address these issues, Lyapunov-based approaches have been explored to ensure stability and accelerate LMS algorithm convergence [25]. Additionally, some works have proposed completely replacing the LMS algorithm with support vector machines (SVMs), offering significant performance gains [26]. Hybrid methods have also been explored, combining classical techniques such as PQ and SRF theory with adaptive ADALINE filters [17], [27], [28]. This innovative approach to fundamental component extraction considerably reduces the number of neural networks and parameters to be estimated, optimizes the learning time and computation frequency in real-time implementations, and increases the robustness of these methods.

However, despite these advances, the application of ADALINE-based algorithms in four-wire three-phase systems remains insufficiently explored. Conventional methods continue to be the most commonly used, despite their limitations and disadvantages [29]. Therefore, developing ADALINE-based techniques and exploring their potential in four-wire three-phase systems, could offer a robust alternative to existing methods. This would improve the control of APFs across a wide range of network conditions.

This article proposes a new ADALINE-based hybrid approach for harmonic identification in four-wire networks, aiming to address three major challenges: case study: evaluate the impact of introducing ADALINE into the proposed method by comparing its effectiveness with the PQ theory, which is renowned for its superior performance. Optimal harmonic detection: develop an identification technique capable of effectively detecting all types of harmonics, regardless of network distortion and/or imbalance conditions. Precise identification enables more effective compensation, bringing the total harmonic distortion (THD) closer to zero. Optimal power quality: extract precise reference currents to compensate for harmonic currents, neutral currents, and reactive power, thereby ensuring smooth and stable power and consistent power quality. The proposed method relies on the synchronous detection method (SDM) by replacing the conventional low-pass filter with an ADALINE filter. This innovation overcomes the limitations of traditional SDM and enhances its performance for robust harmonic identification. The effectiveness of the proposed method is evaluated through extensive simulations conducted in the MATLAB-Simulink environment. The simulations encompass various scenarios involving nonlinear and unbalanced single-phase and three-phase loads. The results are then compared to those obtained using instantaneous power theory (PQ theory). The article is structured to provide a clear understanding of the proposed system: section 2 – methodology, details the network configuration, connected loads, and SAPF operation in a four-wire three-phase system, and explains the underlying principles and functionalities of the proposed ADALINE system based on SDM. In section 3 – results and discussion, presents the simulation results, highlighting differences and their implications for improving power quality. Finally, section 4 concludes by summarizing the main contributions of the article and potential future advancements.

2. METHOD

2.1. System description

Figure 1 illustrates the configuration of the electrical network studied. A three-phase power source with a neutral wire feeds a set of nonlinear loads divided into two groups. To improve power quality and mitigate problems caused by harmonics, a three-phase, four-leg voltage source inverter is connected in parallel to these loads at the point of common coupling (PCC). This configuration functions as a shunt active power filter (SAPF). This type of filter is particularly effective for compensating harmonic currents and neutral currents in nonlinear and unbalanced electrical systems. The four-leg SAPF effectively reduces THD to meet IEEE-519 standards.

Unlike the three-leg SAPF, the four-leg SAPF also provides a neutral current path, allowing for the attenuation of unbalanced currents. The inverter is powered by an 800 V DC voltage source, which allows for the regulation of the power supplied by the inverter and facilitates easy modulation of the amplitude and frequency of the AC output current. The inverter's switching pulses are generated using a hysteresis band current controller (HBCC), which ensures precise and rapid tracking of current variations. The HBCC maintains the inverter's output current within a predefined band around the reference value by adjusting the control pulses to minimize deviations. This controller is particularly suitable for managing rapid variations and maintaining the stable performance of the APF, even in the presence of fluctuating nonlinear loads. In our configuration, the hysteresis band amplitude is 0.01 A.

Table 1 summarizes the system parameters, while Table 2 details the characteristics of the chosen loads. Two load scenarios were considered to reflect the diversity and complexity of real electrical networks. Case (1) represents a general electrical network, also known as a connected or online network, typically composed of various types of three-phase and single-phase loads. Case (2) describes an islanding network, also known as an offline network or a microgrid, mainly composed of single-phase loads.

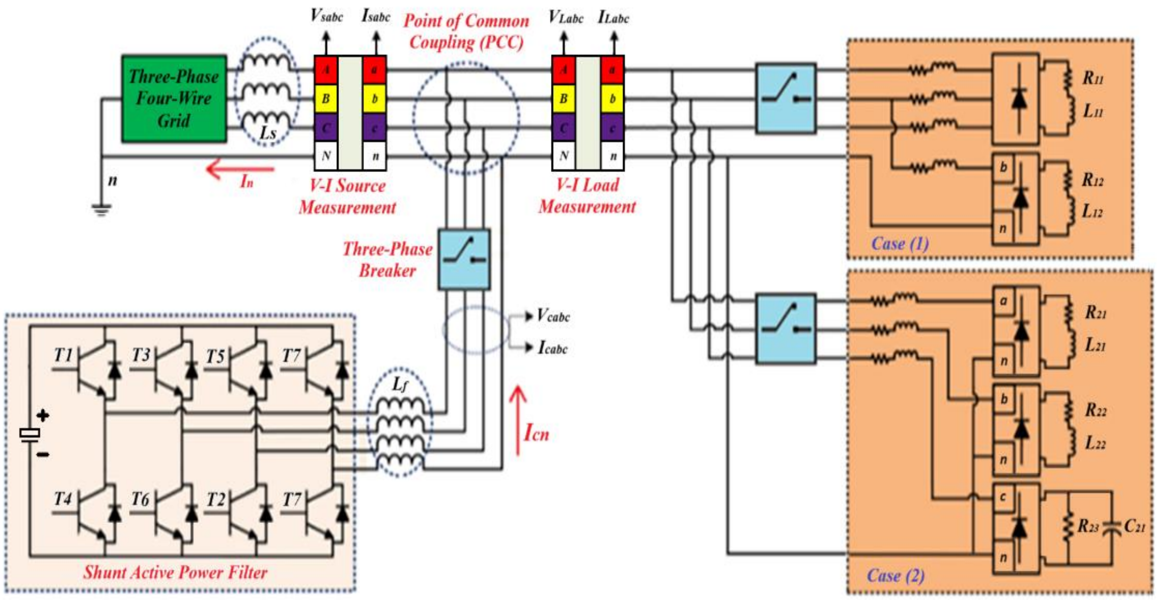

Figure 1. Proposed system topology

Table 1. The proposed system parameters

Elements	Values
Voltage and frequency	230 V, 50 Hz
Source resistance (R_s) and induction (L_s)	0.42 Ω, 19.8 mH
Filter resistance (R_f) and induction (L_f)	1 mΩ, 15 mH
DC source	800 V
HBCC band	0.01 A
Switching frequency (fsw)	10 kHz

Table 2. Load parameter for each scenario

Load configuration	Load type	Details
Case (1)	3ΦNLL Phase (abc)	R_{11} = 30 Ω, L_{11} = 50 mH, In series.
	1ΦNLL Phase (b)	R_{12} = 20 Ω, L_{12} = 35 mH, In series
Case (2)	Phase (a)	R_{21} = 27 Ω, L_{21} = 85 mH, In series
	Phase (b)	R_{22} = 40 Ω, L_{22} = 50 mH, In series
	Phase (c)	R_{23} = 83 Ω, C_{21} = 1650 µF, In parallel

2.2. Synchronous detection method

The SDM stands out for its simplicity and reliability in isolating the fundamental components of signals in disturbed electrical networks, whether balanced or unbalanced. Its robustness against noise and voltage distortions makes it particularly appealing, avoiding complex calculations [30]. In this method, the three-phase source currents are assumed to be balanced after compensation. The real power $P(t)$ consumed by the load can be calculated from the instantaneous voltages (v_{sa}, v_{sb}, and v_{sc}) and load currents (i_{La}, i_{Lb}, and i_{Lc}), as illustrated by (1).

$$P(t) = \begin{bmatrix} v_{sa} & v_{sb} & v_{sc} \end{bmatrix} \begin{bmatrix} i_{La} \\ i_{Lb} \\ i_{Lc} \end{bmatrix} \tag{1}$$

Next, the average value P_{dc} is determined by applying $P(t)$ to a low-pass filter. Thus, the real power is distributed among the three phases according to the (2):

$$P_a = P_{dc}\left(\frac{U_{am}}{U_{am}+U_{bm}+U_{cm}}\right), P_b = P_{dc}\left(\frac{U_{bm}}{U_{am}+U_{bm}+U_{cm}}\right), P_c = P_{dc}\left(\frac{U_{cm}}{U_{am}+U_{bm}+U_{cm}}\right) \tag{2}$$

where U_{am}, U_{am}, and U_{am} are the amplitudes of v_{sa}, v_{sb}, and v_{sc} respectively. From these values, the balanced line currents can be determined as (3):

$$I_a(t) = 2v_{sa}\left(\frac{P_a}{U_{am}{}^2}\right), I_b(t) = 2v_{sb}\left(\frac{P_b}{U_{bm}{}^2}\right), I_c(t) = 2v_{sc}\left(\frac{P_c}{U_{cm}{}^2}\right) \tag{3}$$

finally, the reference currents are defined by (4)-(6).

$$I_{aref}(t) = I_a(t) - i_{La}(t) \tag{4}$$

$$I_{bref}(t) = I_b(t) - i_{Lb}(t) \tag{5}$$

$$I_{cref}(t) = I_c(t) - i_{Lc}(t) \tag{6}$$

Despite its simplicity and robustness, the adoption of SDM in APFs remains limited due to its perceived lower accuracy compared to other traditional methods. Studies [31], [32] have particularly highlighted limitations in terms of THD reduction compared to techniques such as PQ theory. Additionally, SDM has constraints related to response time and stability. While PQ theory allows for compensation in a single cycle, SDM calculations can extend over several cycles (up to fourteen at 50 Hz) [30]. These limitations partly explain the relative lack of interest from the scientific community in this method. To address these limitations while retaining the advantages of SDM, we propose replacing the conventional low-pass filter, known for its sensitivity to noise, with an ADALINE filter. The learning and adaptation capabilities of ADALINE should significantly improve the precision and convergence speed of SDM. A detailed description of ADALINE will be presented in the following section. Figure 2 illustrates the structure of the SDM incorporating ADALINE.

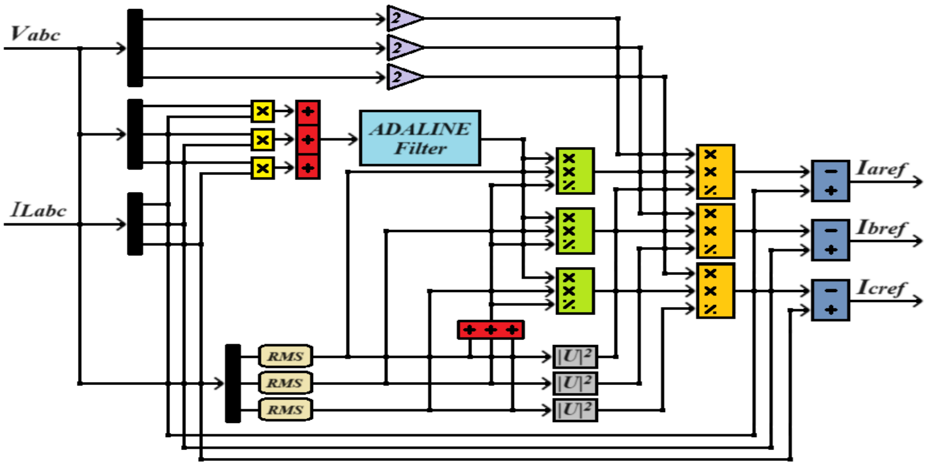

Figure 2. Proposed ADALINE-based SDM topology

2.3. Adaptive linear neurone (ADALINE)

The ADALINE is a simple yet powerful neural network introduced by Bernard Widrow and Ted Hoff in 1960. This network is widely used in signal processing and adaptive filtering applications, particularly for the estimation of frequency, fundamental, and harmonic components. It is capable of handling both linear and nonlinear signals [18], [33]. The ADALINE consists of a single layer of neurons using a linear activation function.

Its operation is based on the weighting and summation of inputs. Each input component «X_k» is multiplied by a corresponding synaptic weight «W_k», forming a weighted product « $X_k W_k$». The sum of these weighted products constitutes the estimated output « y_{est}». The weights are adjusted during the learning process, to minimize the error «e» between the desired output «y_d» and the estimated output « y_{est}». The structure of the proposed ADALINE is presented in Figure 3. In our study, we integrated an ADALINE with the SDM to improve the accuracy of real power filtering and efficiently extract the fundamental component. It was implemented in MATLAB/Simulink using the "S-Function Builder" block and programmed in the C language.

To adapt the ADALINE to the non-linearity of our system and determine its parameters, we used the Fourier series decomposition of the studied signal. This decomposition allows expressing the signal as a sum of sinusoids at multiples of the fundamental frequency. The fourier coefficients corresponding to the frequencies of interest $\cos(2\pi kft)$ and $\sin(2\pi kft)$ are used as inputs to the ADALINE. The amplitudes of these components a_k and b_k, which we aim to estimate, are considered as the synaptic weights to be adjusted. The fourier series decomposition equation is presented as (7):

$$y = \sum_{k=1,2}^{\infty} [a_k \, sin(2\pi kft) + b_k \, cos(2\pi kft)] \quad (7)$$

The estimated output « y_{est}» can be expressed by (8):

$$y_{est} = \sum_{k=1,2}^{\infty} (W_k . X_k) = W^T . X \quad (8)$$

The input vector «X» is defined as (9):

$$X = [1 \;\; \sin(2\omega t) \;\; \cos(2\omega t) \;\; \sin(4\omega t) \;\; \cos(4\omega t) \;\; \dots \;\; \sin(k\omega t) \;\; \cos(k\omega t)] \quad (9)$$

While the weight vector «W^T» is given as (10):

$$W^T = [w_0 \;\; w_1 \;\; w_2 \;\; w_3 \;\; w_4 \;\; \dots \;\; w_{k-1} \;\; w_k]^T \quad (10)$$

To adjust the synaptic weights, we use the least mean squares (LMS) learning algorithm. This algorithm updates the weights at each iteration based on the quadratic error between the desired/real output and the estimated output. The update rule is given by (11).

$$W(k+1) = W(k) + \mu . e(t) . X(k) \quad (11)$$

Where: $W(k+1)$ is the updated weight vector at iteration k+1, $W(k)$ is the weight vector at iteration k, μ is the learning rate, $e(t)$ is the error between the desired output and the estimated output. It is equal to $(y_d - y_{est})$. Finaly, $X(k)$ is the input vector at iteration k. The learning process continues until the error converges to a minimum, indicating that the model has learned the optimal weights for the given task. The estimated fundamental power is then evaluated as (12):

$$P_{dc}(t) = W_{a1} \sin \omega t + W_{b1} \cos \omega t \tag{12}$$

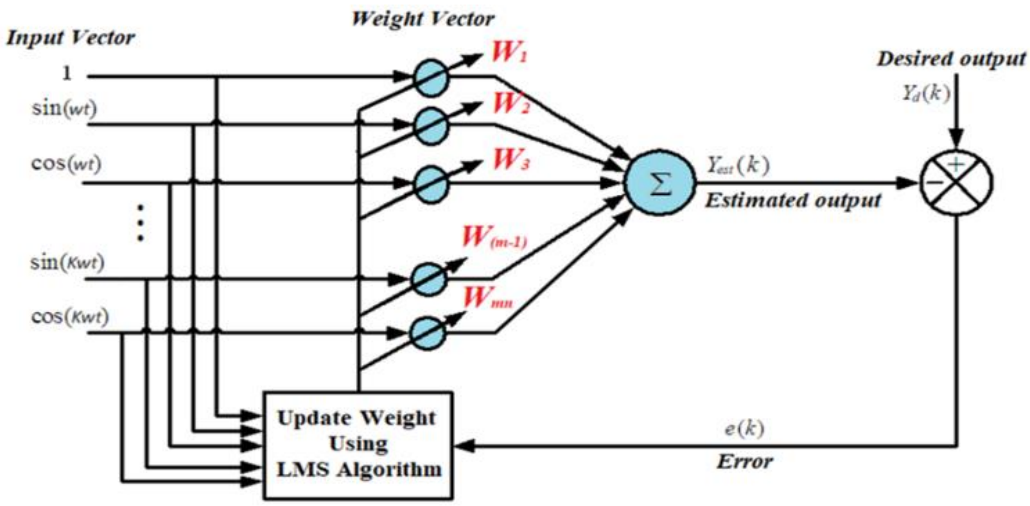

Figure 3. Proposed ADALINE topology

2.4. Instantaneous power theory

One widely used method for harmonic identification is the IPT, also known as p-q theory. This technique is extensively applied for analyzing and controlling power systems, particularly in APFs [5], [34]. Developed by Akagi, Kanazawa, and Nabae in 1983 [35], IPT has become a cornerstone in the field of power quality improvement. The core concept of IPT involves transforming three-phase voltages and currents from the time domain to the instantaneous power domain using the Clarke transformation. This transformation, as shown in (13), converts voltages and currents from the abc frame to the αβ frame.

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \text{ and } \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \tag{13}$$

This transformation allows the separation of the power components into active and reactive power, which can then be further analyzed to identify harmonic distortions and imbalances in the system. The instantaneous active power $p(t)$ and instantaneous reactive power $q(t)$ are given in (14):

$$\begin{bmatrix} p \\ q \end{bmatrix} = \begin{bmatrix} v_\alpha & v_\beta \\ -v_\beta & v_\alpha \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} \tag{14}$$

after applying low-pass filtering to the previously obtained powers, the reference currents to be supplied by the SAPF in the two-phase (αβ) frame are given by (15):

$$\begin{bmatrix} i_{r\alpha} \\ i_{r\beta} \end{bmatrix} = \frac{1}{v_\alpha^2 + v_\beta^2} \begin{bmatrix} v_\alpha & -v_\beta \\ v_\beta & v_\alpha \end{bmatrix} \begin{bmatrix} p_c \\ q_c \end{bmatrix} \tag{15}$$

to eliminate harmonics and reactive power, the unwanted powers chosen to be eliminated are given in (4):

$$\begin{cases} p_c = \tilde{p} \\ q_c = \bar{q} + \tilde{q} \end{cases} \tag{16}$$

where $\tilde{p}$ is the harmonic active power, and $\bar{q}$ and $\tilde{q}$ are the continuous and harmonic reactive power, respectively. Thus, from (16), the current references in (15) will be as shown in (17):

$$\begin{bmatrix} i_{r\alpha} \\ i_{r\beta} \end{bmatrix} = \frac{1}{v_\alpha^2+v_\beta^2}\begin{bmatrix} v_\alpha & -v_\beta \\ v_\beta & v_\alpha \end{bmatrix}\begin{bmatrix} \tilde{p} \\ \bar{q}+\tilde{q} \end{bmatrix} \tag{17}$$

finally, the inverse Clarke transformation will be applied to (17) to obtain the current references in the abc frame.

3. RESULTS AND DISCUSSION

This section presents and analyzes the results of the numerical simulations of the electrical system, detailed in section 2. These simulations were conducted by comparing two identification methods: the SDM based on an ADALINE algorithm and the traditional PQ method using a 30 Hz low-pass filter. The objective was to validate the hypotheses formulated in the introduction. The evaluation focuses on several performance indicators: the THD rate, the amplitudes of the 3rd, 5th, and 7th order harmonics, the source and neutral currents, as well as the active and reactive power delivered by each method. This comparative analysis allows for an appreciation of the advantages and limitations of each approach within the context of our study. Figure 4 illustrates the simulation results of the load currents, neutral current, and active and reactive power, under the load conditions of scenario (1), main grid, before compensation. These results clearly show that the load currents are highly distorted as shown in Figure 4(a), due to the presence of a three-phase nonlinear load. Additionally, the introduction of an additional single-phase load connected to phase (b) results in a significant increase in the current amplitude in this phase, causing a substantial imbalance between the phases. Moreover, the neutral current reaches high values (20A) and exhibits significant oscillations as shown in Figure 4(b). These disturbances have a direct impact on power, both active and reactive as shown in Figure 4(c), which shows fluctuations and a lack of stability. The power factor, reduced to 0.8480, highlights the importance of harmonics in this case.

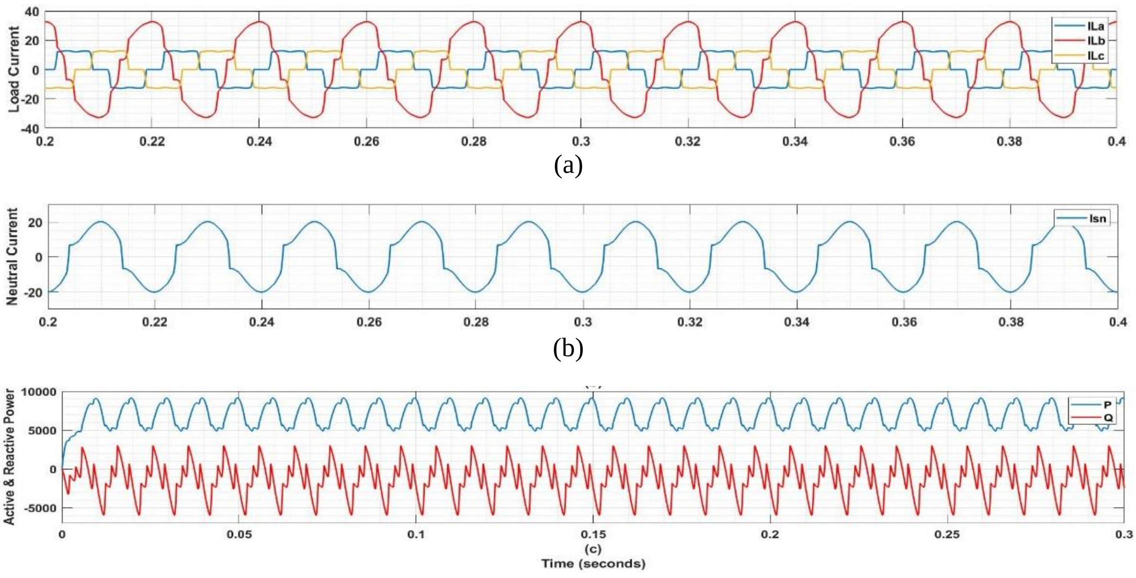

Figure 4. Before compensation signals in case (1): (a) load currents, (b) neutral current, and (c) active power (blue) and reactive power (red)

Figure 5 presents a detailed comparison of the results obtained after compensating the disturbances using the two methods studied: the classical PQ theory (left column) and the neural SDM (right column). The quantities compared include the source currents, the phase shift between the source voltage and current, the neutral current, as well as the active and reactive power. This comparative analysis evaluates the advantages and limitations of each approach in terms of compensation quality and energy efficiency. Both methods ensure effective and almost identical compensation, producing sinusoidal and balanced source current waveforms with a 120-degree phase shift between the three phases as shown in Figures 5(a) and 5(a'), and in phase with the voltage as shown in Figures 5(b) and 5(b'), resulting in a power factor close to unity. However, the SDM stands out from the PQ theory in two aspects: first, by a higher source current amplitude, reaching 40 A compared to 20 A for the PQ theory; second, by a perfect balance of these current amplitudes, unlike a slight persistent imbalance in the amplitude of phase (b) of about 4% compared to the other phases. Both methods ensure a negligible neutral current as shown in Figures 5(c) and 5(c'). Regarding active and reactive power as shown in Figures 5(d) and 5(d'), both methods succeed in fully compensating the reactive power. For active power, the PQ theory shows better stability during the transition period but exhibits residual fluctuations of about 2.2% around the average value in steady-state. In contrast, the neural SDM method, although disturbed during the transient phase, offers perfect stability and smooth active power in a steady state, with an average amplitude of 15 kW. The response time of both methods is similar, around 0.04 s, which marks an improvement in SDM performance compared to the results reported in [30]. This superior stability of the SDM is crucial for applications requiring a high-quality electrical power supply.

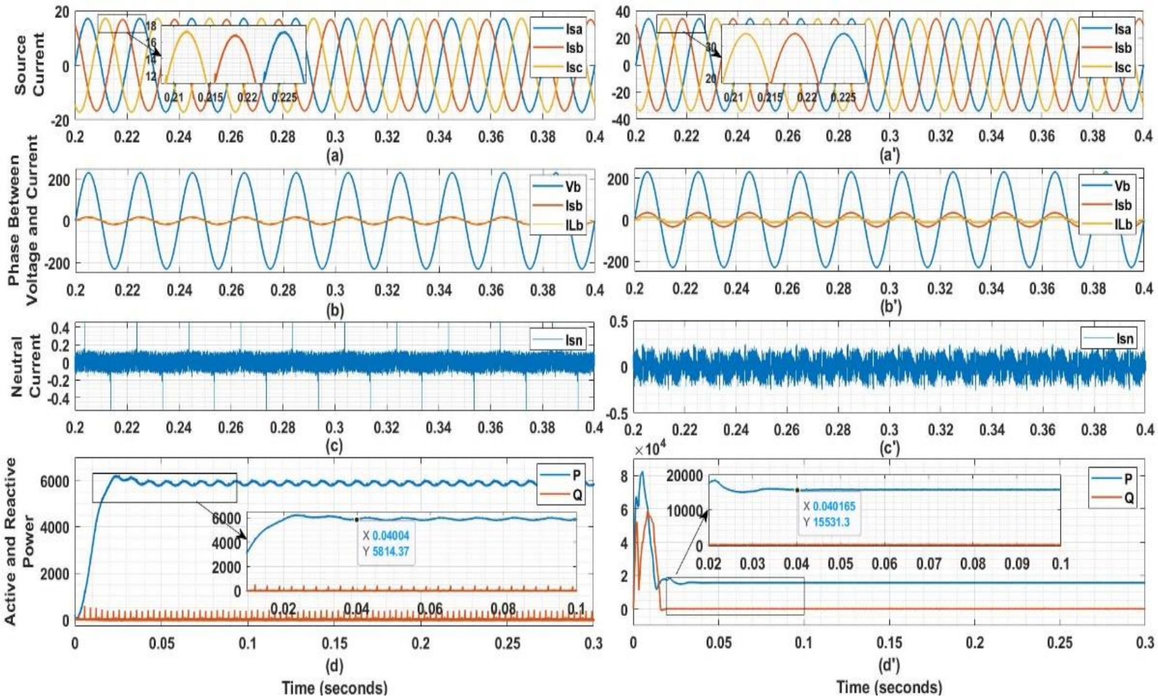

Figure 5. Post-compensation signal in case (1): source current (a) PQ theory, (a') SDM; Phase between voltage and current, (b) PQ theory, (b') SDM; neutral current, (c) PQ theory, (c') SDM, active and reactive power, and (d) PQ theory, (d') SDM

However, although these graphical results seem to favor the proposed SDM, they are not sufficient to prove its superiority over the PQ theory. A detailed study of the harmonic spectrum, particularly the THD rate as well as the 3rd, 5th, and 7th order harmonics, is therefore necessary. Table 3 summarizes these results before and after compensation, allowing for more robust conclusions regarding the overall performance of each method. The two identification methods explored in this study achieve THD values compliant with the IEEE-519 standard. However, their effectiveness varies, as shown in Table 3. While the PQ theory shows a promising reduction in THD, the neural SDM consistently offers the most impressive results, achieving a significantly lower THD than the PQ theory. This superior performance also extends to the reduction of 3rd, 5th, and 7th order harmonics. The neural SDM consistently achieves THD percentages below 0.5% for all three phases. The THD is reduced from 26.90% to just 0.36% for phase (a), from 14.30% to 0.37% for phase (b), and from 26.72% to 0.36% for phase (c). The 5th and 7th order odd harmonics, which are the most harmful in this type of system, comply with relevant standards, with values below 0.1%. Similarly, the 3rd order harmonic, which appears only in the unbalanced phase (b), is reduced from 6.16% to a remarkable 0.03%. These results highlight the effectiveness of ADALINE in improving the accuracy and robustness of the SDM, also demonstrating the superior ability of the neural SDM to mitigate harmonics and improve current waveform quality.

Table 3. Case (1) results

		Norme	Before compensation	PQ theory	Neural SDM
Phase (a)	THD%	<5%	26.90	1.06	0.36
	h3/h1 (%)	<4%	0.28	0.04	0.04
	h5/h1 (%)	<4%	20.47	0.28	0.10
	h7/h1 (%)	<4%	12.63	0.23	0.07
Phase (b)	THD%	<5%	14.30	1.11	0.37
	h3/h1 (%)	<4%	6.16	0.06	0.03
	h5/h1 (%)	<4%	8.13	0.22	0.08
	h7/h1 (%)	<4%	4.62	0.18	0.06
Phase (c)	THD%	<5%	26.72	1.02	0.36
	h3/h1 (%)	<4%	0.10	0.05	0.01
	h5/h1 (%)	<4%	20.16	0.26	0.11
	h7/h1 (%)	<4%	12.77	0.22	0.07

Although single-phase nonlinear loads tend to cause imbalances in connected networks (online networks), the presence of symmetrical three-phase loads plays a significant mitigating role. Indeed, as illustrated in the previous scenario, the percentage of 3rd order harmonic, indicative of imbalances, does not exceed 7%, a value close to the regulatory limit of 4%. According to the data from [36], this type of harmonic in these networks can reach a limit of 15%. This result highlights the stabilizing role of three-phase loads. In contrast, offline networks, characterized by a predominance of single-phase loads, are more vulnerable to harmonic distortions, particularly the 3rd order harmonic which can reach alarming levels. The absence of a natural attenuating effect in these networks necessitates a thorough evaluation of our method in this specific context. The simulation results of scenario (2), presented in Figure 6, reveal a significant degradation in signal quality before compensation compared to scenario (1). Single-phase nonlinear loads introduce significant and uneven distortions and imbalances in the load currents as shown in Figure 6(a), these effects depend on the type of single-phase load connected to each phase and the current demand. Moreover, the neutral current exhibits considerable fluctuations, with peak values reaching 10 A as shown in Figure 6(b). Although these loads consume less power than three-phase loads, resulting in lower active and reactive power amplitudes compared to scenario (1), they fluctuate considerably as shown in Figure 6(c). These disturbances lead to a drastic reduction in the power factor, reaching 0.5353, and decrease the efficiency of power transfer.

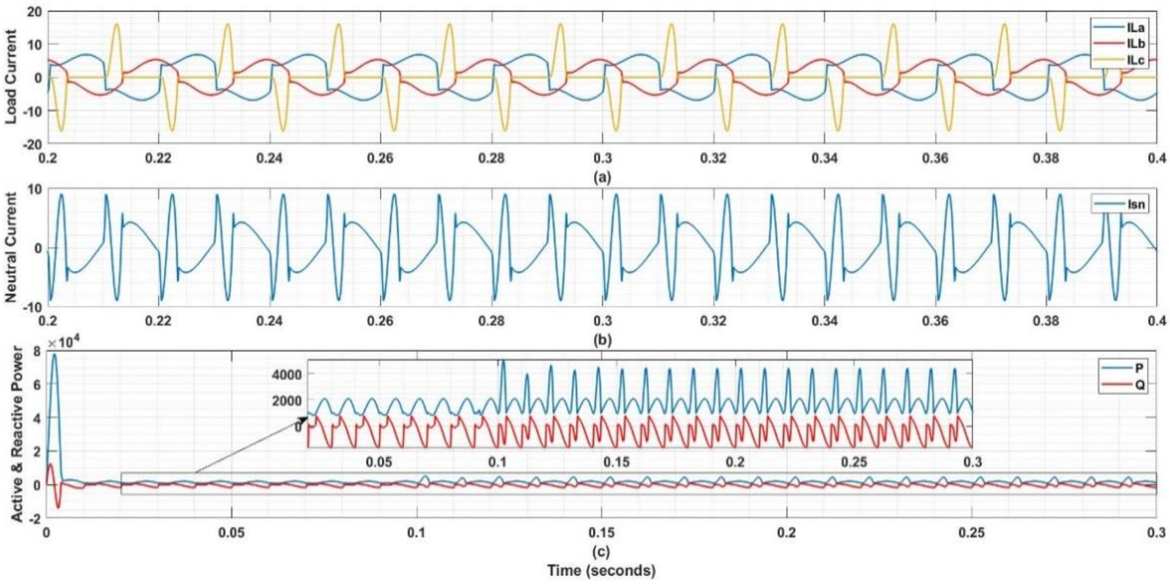

Figure 6. Before compensation signals in case (2): (a) load currents, (b) neutral current, and (c) active power (blue), and reactive power (red)

Figure 7 presents the signals of the two methods studied (neural SDM and PQ theory) after compensation in scenario (2). Except for the powers, the waveform results of the source currents and neutral currents obtained in this scenario are almost identical to those in the previous scenario. The source currents are sinusoidal, balanced, and phase-shifted by 120 degrees as shown in Figures 7(a) and 7(a'), while being perfectly synchronized with the voltages as shown in Figures 7(b) and 7(b'), resulting in a unit power factor. The amplitudes of these currents are lower than those in the first scenario, with the SDM method reaching 10 A, while the PQ theory reaches 5 A. This is because single-phase loads consume less current than three-phase loads. However, a slight asymmetry in the phase amplitudes, around 0.2%, is observed for the PQ theory, unlike the neural SDM, which offers perfect symmetry, indicating precise identification by this method. The neutral current is almost zero, less than 0.5 A in both methods as shown in Figures 7(c) and 7(c'), indicating effective harmonic compensation. Regarding active and reactive power; both methods ensure total compensation of reactive power. However, the behavior of active power differs between the two approaches as shown in Figures 7(d) and 7(d'). The response of the proposed method is faster than that of the PQ theory; despite transient disturbances, the ADALINE-based SDM reaches a steady state in just 0.07 seconds, compared to 0.12 seconds for the PQ theory. Additionally, the SDM offers superior power quality, perfectly stable and smooth, with an amplitude of 5209 W, giving it a significant performance advantage. This power stability, combined with high-quality power supply, makes this method an ideal tool for electronic devices, household appliances, and other renewable energy sources common in the tertiary and domestic sectors of offline networks, as well as for some critical infrastructures more demanding in terms of power quality, such as hospitals and communication systems.

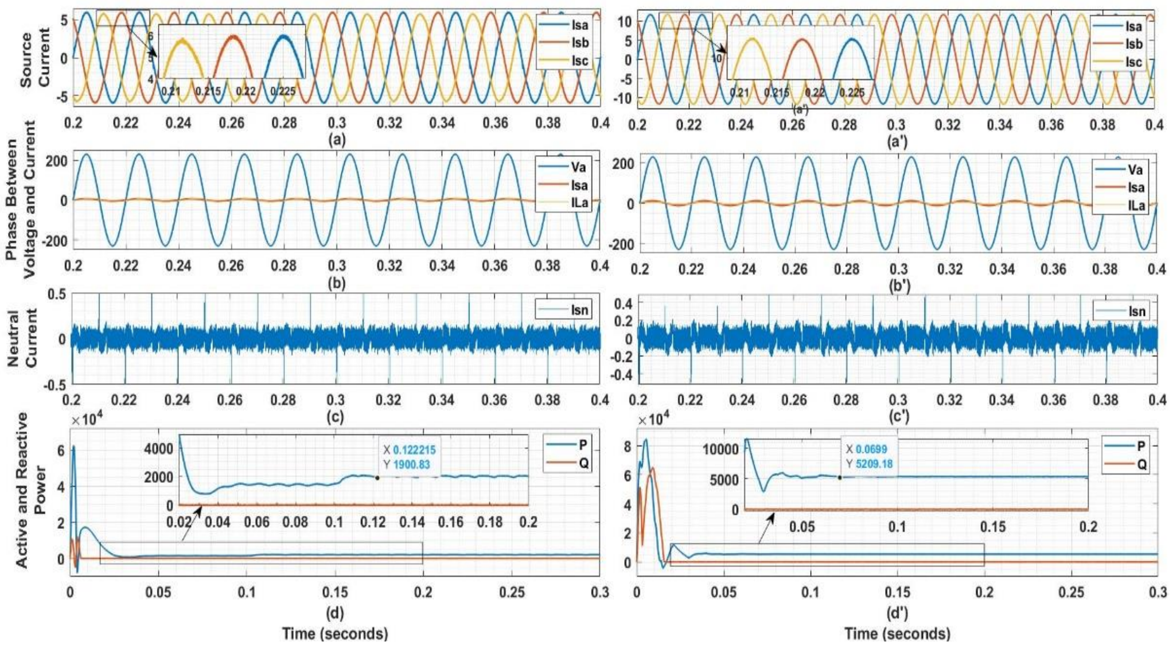

Figure 7. Post-compensation signals in case (2): source current (a) PQ theory, (a') SDM; phase between voltage and current (b) PQ theory, (b') SDM; neutral current (c) PQ theory, (c') SDM, active and reactive power (d) PQ theory, (d') SDM

Table 4 presents a comparative analysis of harmonic specter results before and after compensation, highlighting the identification method's influence on the filtering process's effectiveness. Although the three loads used in the simulation are single-phase and nonlinear, the type of component connected to them plays a crucial role in the impact of these loads on network behavior. Indeed, the highly capacitive load (phase c) induces a significantly higher THD, peaking at 119.96%. Additionally, it records the highest content of the 3rd order harmonic (87.39%), considerably exceeding those of phases (a) (22.26%) and (b) (9.67%). Under these conditions, the third-order harmonic predominates, further aggravating the imbalance and threatening network stability. After compensation, it is clear that the proposed SDM method consistently outperforms the PQ theory. The THD is significantly reduced: from 30.96% to 0.81% (phase a), from 15.04% to 0.75% (phase b), and from 119.96% to only 0.82% (phase c). These exceptional results are markedly better than the higher THD values obtained with the PQ theory: 1.67%, 1.47%, and 1.57%, respectively. The superior performance of the ADALINE-based method also extends to the attenuation of individual 3rd, 5th, and 7th order harmonics, demonstrating its exceptional precision and harmonic detection capabilities. This success is attributed to ADALINE, which enhances the SDM. The percentages of odd 3rd order harmonics are remarkably low, ranging from 0.08% to 0.02% and 0.14% for each phase, attesting to the efficiency of this method.

Table 4. Case (2) results

		Norme	Before compensation	PQ theory	Neural SDM
Phase (a)	THD%	<5%	30.96	1.67	0.81
	h3/h1 (%)	<4%	22.26	0.16	0.08
	h5/h1 (%)	<4%	13.68	0.15	0.06
	h7/h1 (%)	<4%	9.73	0.15	0.06
Phase (b)	THD%	<5%	15.04	1.47	0.75
	h3/h1 (%)	<4%	9.67	0.03	0.02
	h5/h1 (%)	<4%	6.73	0.08	0.03
	h7/h1 (%)	<4%	5.03	0.04	0.02
Phase (c)	THD%	<5%	119.96	1.57	0.82
	h3/h1 (%)	<4%	87.39	0.22	0.14
	h5/h1 (%)	<4%	65.87	0.33	0.19
	h7/h1 (%)	<4%	41.51	0.24	0.17

In summary, this study demonstrated the feasibility of developing a method for detecting harmonics in four-wire electrical networks that is more accurate than conventional approaches. By leveraging the advantages of ADALINE, we successfully overcame the challenges posed by the distortions and imbalances inherent in these systems. This new approach, which combines the simplicity of the SDM with the power of ADALINE, offers a precise, robust, and efficient solution for harmonic identification in both online and offline networks, thus validating the first objective. Secondly, this hybrid approach provides an optimal solution for harmonic detection. By generating a reference current with unparalleled precision, it enables the SAPF to compensate for harmonics extremely effectively. These performances are confirmed by the very low total and individual THD values approaching zero, as presented in Tables 3 and 4 for the two scenarios considered. This also validates the third objective, which is to achieve optimal power quality. Figures 6 and 7 confirm that, thanks to the proposed SDM, it is possible to ensure stable and consistent active power with a rapid response time, total compensation of reactive power and neutral current, as well as perfectly sinusoidal and balanced source currents. It is thus clear that the ADALINE algorithm plays a crucial role in enhancing the performance of this method, making the ADALINE-based SDM a potential alternative for managing the operation of SAPFs in a three-phase four-wire system, rather than relying solely on conventional techniques such as PQ theory. Although the simulation results are encouraging, this study has two limitations. First, an in-depth comparative study is necessary to evaluate the performance of neural SDM compared to the direct ADALINE method and other hybrid approaches based on ADALINE. Furthermore, experimental validation is required to demonstrate the feasibility of real-time implementation of the proposed method. These two areas will be the focus of future work.

4. CONCLUSION

In this article, we demonstrated the feasibility and effectiveness of a new method for detecting harmonics in four-wire three-phase electrical networks. The proposed method is based on a hybrid process that combines the SDM and the adaptive ADALINE algorithm. Extensive simulations and analyses conducted using MATLAB/Simulink under heavily distorted and unbalanced network conditions allowed us to compare the performance of our method to that of the PQ method, which is the reference in this field. The results obtained significantly demonstrate the superiority of our approach compared to conventional techniques. The neural SDM offers better stability and superior active power quality in steady state compared to the PQ method. It also significantly reduces the THD rate, as well as the 3rd, 5th, and 7th order harmonics, in accordance with IEEE-519 standards, achieving values below 1% for all three phases, which is markedly better than the results obtained with the PQ method. This method ensures perfectly sinusoidal, balanced, and synchronized source currents, as well as total compensation of reactive power and excessive neutral current, with a rapid response time (0.04 – 0.07 s), resulting in a unit power factor. These exceptional performances are attributed to the integration of the adaptive ADALINE algorithm, which enhances the accuracy of the generated reference currents and robustness against noise and disturbances in the SDM. This new hybrid approach provides a simple, precise, robust, and high-performance solution for harmonic identification during APF compensation, both for online and offline networks. It represents a potential alternative to conventional techniques and could be particularly beneficial for applications requiring high-quality power supply, such as critical infrastructure. Future work will focus on more in-depth comparative studies and the experimental validation of the method under real-world conditions.

ACKNOWLEDGEMENTS

This work was supported by the Algerian general direction of research DGRDT. The authors would like to express their sincere gratitude.

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