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Artificial Neural Network Based Shunt Active Power Filter for Power Quality Improvement

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Abstract— The increase in non-linear loads in the electrical distribution system has resulted in harmonics, which affect the power system's stability and performance. The project focuses on mitigating the current harmonics of the system by implementing a Shunt Active Power Filter (SAPF), optimized using an Artificial Neural Network (ANN). The proposed system ensures the generation of compensating current through the Shunt Active Power Filter (SAPF), which helps in mitigating the harmonics present in the system. The project showcases the gradual improvement in power quality using different techniques for optimization in the conventional Shunt Active Power Filter (SAPF). This paper presents a comparative analysis of harmonic reduction techniques for a non-linear load system. The uncompensated system shows a Total Harmonic Distortion (THD) of 28.34%. Applying a conventional Shunt Active Power Filter (SAPF), PI-tuned SAPF, and PSO-optimized PI-SAPF reduces THD to 14.01%, 3.43%, and 1.64%, respectively. An Artificial Neural Network (ANN) further enhances the PSO-PI controller through adaptive real-time optimization. MATLAB/Simulink simulations demonstrate the proposed ANN-based SAPF achieves a THD of 1.41%, offering superior harmonic suppression compared to traditional methods. This demonstrates the significant improvement in the power quality by effectively mitigating the harmonics present in the system.

Keywords — shunt active power filter (SAPF), artificial neural network (ANN), back propagation, total harmonic distortion, PI controller, (THD), particle swarm optimization (PSO), PQ theory

I. Introduction

A power grid is a network that delivers electricity from producers to consumers through components such as generation stations, transmission lines, substations, and distribution lines. Its main purpose is to provide a consistent and reliable power supply to end users, including households and industries, which connect to various electrical loads. Loads can be linear or non-linear: linear loads, such as lamps and heaters, draw current that follows the same sinusoidal pattern as the voltage, while non-linear loads distort the current waveform.

In recent years, the use of nonlinear electronic loads such as compact fluorescent lamps (CFLs), computers, televisions, etc has increased significantly. Nonlinear loads inject harmonic currents into the distribution network [1]. Harmonics are defined as deviations from the fundamental frequency sine wave. They are expressed as sine waves of frequencies that are multiples of the generated frequency. Harmonics cause stress on the transformers and generators that make up the power system also known as the power grid.

Therefore, it is extremely important to correctly measure the harmonic disruption in the electrical network. In order to detect these problems, modelling and analysis of power systems are of great importance [2]. Total Harmonic Distortion (THD) is one of the most important measurement indices used in these standards to evaluate quality in power systems systematically and comparably, thus helping to improve power system quality and reduce distortion levels [3].

With the development in computational technologies, artificial intelligence (AI) techniques, such as fuzzy logic (FL), artificial neural network (ANN) (see Section C and F), particle swarm optimization (PSO) (Section E), etc. have recently been applied widely in various electronic and drive applications. Studies have demonstrated the effectiveness of PSO in optimizing the gains of a PI controller in SAPF DC-link voltage regulation [21]. Conventional control methods have lengthy response times due to the processing time necessary to execute complex systems. However, with ANN, the complexity and hence the processing time requirement are reduced, thereby offering a faster response [4].

Attempts at filter design automation have been made since the 1990s, when Higuchi et al. introduced the concept of

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evolvable hardware. The majority of these strategies used Genetic Algorithms (GA) and produced some promising outcomes [5]. Though GA can optimize filters, the results are sometimes overly complicated and difficult to deploy. Adopting Passive Filters or using centralized active power filters are the traditional methods to limit the harmonics in the system. A number of works were published around 2008 on the applications of passive filters for the improvement in power quality in different electrical systems [6].

In 2009, W. Zhao and G. Chen suggested an LCL-type filter with a sufficient attenuation ratio for switching ripple and modest LC parameters, suitable for usage as an output filter. However, LC-filter, as a third-order resonant circuit itself, is difficult to be stable [7]. Although the passive filter is simple and inexpensive, it has significant drawbacks. One example is that because the harmonics that need to be suppressed are of low order, the filter components used are found to be very bulky [8].

As the regulatory requirements became more stringent, the passive filters were not able to meet future revisions of a particular standard. This demanded a retrofit of new filters. An active AC harmonic filter, composed of high-frequency inverters and a series-resonant LC circuit tuned to the fundamental frequency, was proposed by Nakajima et al in order to solve harmonic distortion problems on distribution systems at lower cost and with higher efficiency [9].

Active Power filters are effective harmonic mitigation techniques. An inverter with a voltage source makes up the Shunt Active filter. In 2012, Chovatia et al. explored and used several current control techniques, including fuzzy logic, dead beat control, synchronous reference frame (related to PQ Theory, see Section 1.4), direct control, and hysteresis current control, which are utilized for PWM generation. Harmonic removal might be accomplished easily and effectively with a shunt active filter with VSI architecture. The SAPF's current control mechanism produced outcomes that fell inside the IEEE 519 range [10].

Rajat Sinha's work described the design, simulation, and preliminary analysis of a 3-phase multi-level shunt active power filter to improve power quality by eliminating harmonics. This article explained the filter's performance utilizing instantaneous power theory (PQ Theory, Section D) with PI and a hysteresis current controller [11]. Sahadev et al. compared and evaluated the performance of the shunt active power filter (SAPF) using the PI and FUZZY controllers in 2015 [12]. These PI controller-based SAPFs showed a considerable reduction in Total Harmonic Distortion.

With the development in computational technologies, various optimization techniques have recently been applied widely in various electronic and drive applications. Reddy et al has compared various evolutionary algorithms and swarm intelligence methods in his paper in 2020 [13]. A paper by Y. Alinejad-Beromi et al aims for voltage profile improvement, loss reduction, and THD reduction in distribution networks by using Particle Swarm Optimization (PSO) as the solving tool (Section). The experimental results on this paper show that the proposed PSO method is indeed capable of obtaining higher quality solutions efficiently [14].

Teaching-Learning-Based Optimization (TLBO) is a relatively new, dependable, accurate, and robust optimization technique for global optimization over continuous domains. Rao et al. presented the TLBO algorithm, which is based on the natural process of teaching and learning [15]. Similarly, Naik et al. found that a rough TLBO technique outperformed GA, PSO, and DE in terms of finding optimal features in less time [16]. The goal of this project is to optimize the performance of an ANN-based PI controller utilizing Teaching Learning Based Optimization.

A. *Total Harmonic Distortion (THD)*

It is the ratio of square root of the sum of squares of the rms value of harmonic components to the rms value of the fundamental components. It can also be defined as, the ratio of harmonic component to fundamental in simple words. THD is calculated as a percentage of the fundamental. The higher the proportion, the more distorted the waveform becomes. In an electrical grid system, the primary concern of the electrical supply is voltage harmonics. Typically, in an AC power system, even harmonics are absent, the odd harmonics which are present in an AC system, contribute to Total harmonic Distortion. THD is defined as the ratio of the equivalent root mean square (RMS) voltage of all the harmonic frequencies (from the 2nd harmonic on) over the RMS voltage of the fundamental frequency (the fundamental frequency is the main frequency of the signal, i.e., the frequency that you would identify if examining the signal with an oscilloscope).

B. *Shunt Active Power Filter (SAPF)*

One kind of power filter used to correct for reactive power, unbalanced currents, and current harmonics in a power system is the shunt active power filter (SAPF). It is a popular solution for power quality difficulties caused by nonlinear loads such as fluorescent lighting, variable-speed drives, and power electronics. A generalized block diagram is shown in Figure 1.

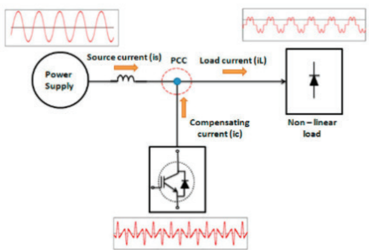

Fig. 1: Block Diagram of a Generalized APF

A SAPF consists of an inverter, a DC-link capacitor, and several power electronic components such as power MOSFETs or insulated gate bipolar transistors (IGBTs). In parallel with the nonlinear load, the inverter injects AC power into the power system by converting DC power from the DC-link capacitor. It adds a set of cancelling harmonics back into the circuit which are meant to counteract the harmonics generated by the nonlinear load. It is economical and more effective than other mitigation methods like adding dc link inductor, or adding an input reactor etc. It protects from noise and power disturbances. It is estimated that THD reduced to 4 to 5% when SAPF is used in the system.

C. *PQ theory*

The instantaneous power theory provides a method for calculating reference compensation currents for active power filters in three-phase systems. It uses the Clarke transformation to convert three-phase voltages (V_a, V_b, V_c) and load currents (i_a, i_b, i_c) from a-b-c coordinates to stationary α-β coordinates:

$$\begin{bmatrix} V_\alpha \\ V_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} * \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} * \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} (2)$$

Instantaneous real power (P) and instantaneous imaginary power (q) in the α-β frame are defined as:

$$\begin{bmatrix} P \\ q \end{bmatrix} = \begin{bmatrix} V_\alpha & V_\beta \\ -V_\beta & V_\alpha \end{bmatrix} \begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix} \quad (3)$$

These instantaneous powers can be separated into average (DC) and oscillating (AC) components:

$$P = \bar{P} + \tilde{P} \quad (4)$$

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

$(\bar{P})$: Average real power, related to the fundamental active current.

$(\tilde{P})$: Oscillating real power, associated with harmonic currents and unbalanced conditions.

$(\bar{q})$: Average imaginary power, related to the fundamental reactive power.

$(\tilde{q})$: Oscillating imaginary power, associated with harmonic currents and unbalanced conditions.

The compensation approach typically involves removing the oscillating real power $(\tilde{P})$ and the entire imaginary power ($q = \bar{q} + \tilde{q}$) to achieve balanced, sinusoidal source currents. The required compensation currents in the α-β frame ($I_{c\alpha}, I_{c\beta}$) are calculated from the power components to be compensated. The compensation strategy often involves eliminating the oscillating real power $(\tilde{P})$ and the entire imaginary power $(q = \bar{q} + \tilde{q})$ to achieve balanced, sinusoidal source currents at unity power factor. The required compensation currents in the \alpha-\beta frame $(I_{c\alpha}, I_{c\beta})$ are derived from the power components to be compensated. For example, to compensate for $\tilde{P}$ and q, the reference currents are calculated based on these components.

D. *Particle Swarm optimization*

The velocity update is the core of the PSO algorithm, influenced by the particle's own best-known position and the entire swarm's best-known position:

$$\boldsymbol{V}^i(t+1) = w\boldsymbol{V}^i(t) + c_1 r_1 \left(\boldsymbol{pbest}^i - \boldsymbol{X}^i(t)\right) + c_2 \quad (5)$$

Where:

- *w is the inertia weight, controlling the influence of the previous velocity (typically decreases over iterations).*
- *c_1 and c_2 are the cognitive and social coefficients, respectively, weighting the attraction towards the particle's personal best and the global best.*
- *r_1 and r_2 are random numbers uniformly distributed in [0, 1], introducing stochasticity.*
- *$\boldsymbol{pbest}^i$ is the best position found by particle (i) so far (yielding the best objective function value).*
- *$\boldsymbol{gbest}$ is the best position found by any particle in the entire swarm so far.*

The terms $\left(\left(pbest^i - X^i(t)\right)\right)$ and $\left(\left(gbest - X^i(t)\right)\right)$ represent the cognitive and social components of the velocity update, guiding the particle towards promising areas of the search space. The $(pbest^i)$ and $(gbest)$ values are updated in each iteration whenever a particle finds a position yielding a better objective function value.

E. *Artificial Neural Network Algorithm Details*

Artificial Neural Networks (ANNs),are computational models that learn from data. The process of training and using an ANN involves specific algorithmic steps. ANNs are particularly useful for tasks like classification, regression, and pattern recognition. The learning occurs by adjusting connection weights and biases within the network to minimize a loss function, which quantifies the difference between the network's predictions and the actual target values. This optimization is typically performed using gradient-based methods.The core ANN algorithm involves two main phases iterated over many epochs (passes through the training data):

Forward Propagation: Input data passes through the network layer by layer, where each neuron computes a weighted sum of inputs, adds a bias, and applies an activation function (e.g., ReLU, Sigmoid, Tanh) to produce an output.

Backpropagation: The loss between predicted and actual values is computed, and gradients are propagated backward to update weights and biases using optimization algorithms such as gradient descent. This process repeats over multiple epochs until convergence.

Hyperparameters: Set before training — network architecture (layers and neurons), activation functions, learning rate, epochs, batch size, optimization method (SGD, Adam, RMSprop), and regularization (e.g., L1/L2, dropout) to prevent overfitting.

II. Materials and Methods

This section details the methodology employed to develop and evaluate an Artificial Neural Network (ANN) based Shunt Active Power Filter (SAPF) for harmonic mitigation in a power system with nonlinear loads. The overall system structure and workflow are depicted in Figure 2. The primary objective is to detect and minimize harmonic distortion originating from nonlinear loads by implementing an optimized ANN-based control strategy for the SAPF.

The system comprises a three-phase voltage source supplying a nonlinear load, specifically implemented as a three-phase diode rectifier bridge feeding an RL load (60 ohms resistance, 1 mH inductance). This configuration inherently draws non-sinusoidal current, introducing harmonic distortion into the system.

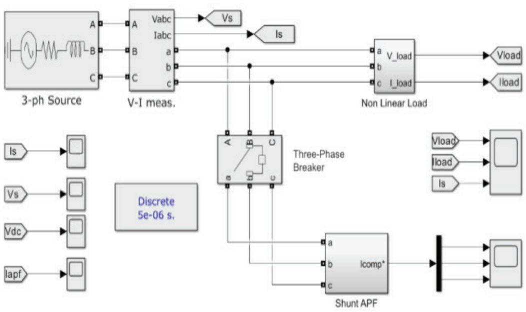

Fig .2 Block Diagram of the Proposed System

A Shunt Active Power Filter (SAPF) is connected in parallel with the load to compensate for these harmonics. The SAPF, implemented using a current source inverter topology (specifically, a universal bridge controlled by gate signals), injects compensating currents into the system to counteract the harmonic currents drawn by the load. The core operation involves generating appropriate reference currents and controlling the SAPF switching to produce the desired compensation. Figure 3 illustrates the conventional SAPF implementation within the simulation environment. It also shows the internal components of the SAPF subsystem block.

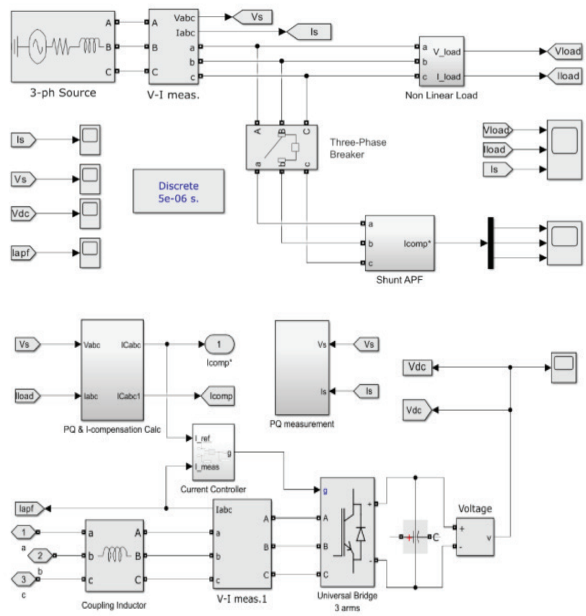

Fig 3: Implementation of a Conventional SAPF in the simulation

Reference current generation is achieved using the instantaneous power (PQ) theory. Source voltages (V_{sabc}) and load currents (I_{labc}) are measured by the VI measurement block. These three-phase quantities are then processed within the "PQ & I Compensation Calculation Block", detailed in Figure 4. Inside this block, the a-b-c voltages and currents are transformed into stationary $\alpha-\beta$ coordinates using the Clarke transformation. These $\alpha-\beta$ components are used to calculate the instantaneous active power (P) and reactive power (Q). The oscillating component of the active power $(\tilde{P})$ and the total reactive power (Q) are typically the targets for compensation. These power components, along with the $\alpha-\beta$ voltage components, are used to calculate the necessary compensation currents in the $\alpha-\beta$ frame. Finally, an inverse Clarke transformation converts these back into three-phase reference currents (I_{Cabc}).

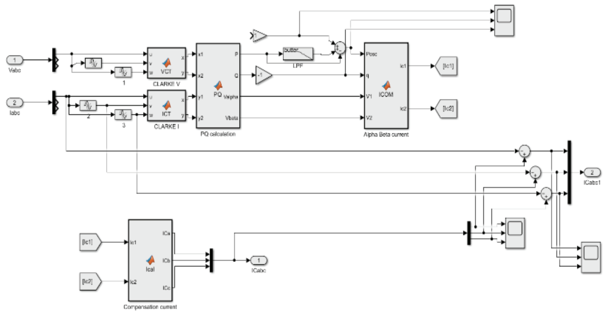

Fig. 4: Inside the PQ & I Compensation Calculation Block.

A hysteresis current controller, shown in Figure 5, is employed to generate the switching signals for the SAPF inverter [17]. This controller compares the generated reference current (I_{Cabc}) with the actual measured filter current injected by the SAPF. If the error between the reference and measured current exceeds a predefined hysteresis band, the controller toggles the switching state of the corresponding inverter leg to force the measured current towards the reference value. This ensures that the SAPF injects the required compensation current within acceptable tolerance limits.

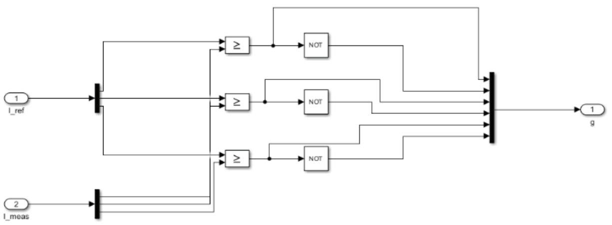

Fig 5: Hysteresis Current Controller implementation

To maintain the DC-link voltage (V_{dc}) of the SAPF at its reference value (e.g., 850V) and account for inverter switching losses, a voltage regulation loop is implemented. The stability and performance of this loop is essential for accurate compensation by SAPF [18]. Initially, a Proportional-Integral (PI) controller is used, as illustrated in Figure 6. The PI controller processes the error between the reference V_{dc} and the measured V_{dc}.Its output, representing the power loss component (P_{loss}), is added to the active power component $(\overline{P})$ within the PQ calculation block (specifically, it adjusts the target $\overline{P}$ that the source needs to supply), influencing the final reference current calculation.

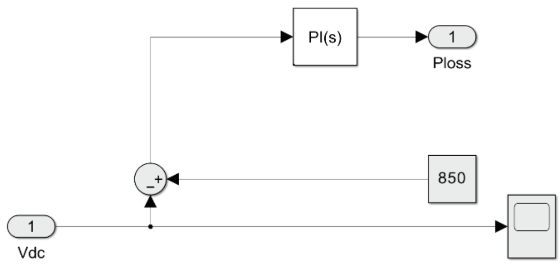

Fig 6: Implementation of the PI Controller for V_{dc} regulation

The performance of the PI controller is highly dependent on its gains $(K_p \, and \, K_i)$. To find optimal values for these gains, Particle Swarm Optimization (PSO) is utilized. The PSO algorithm is configured with a population size of 30 particles, run for a maximum of 30 iterations. The inertia weight (w) dynamically decreases from 0.9 to 0.4 over the iterations, while the cognitive $(c_1)$and social (c_2) weights are set to 1.2 and 1.7, respectively. The search space for K_p and K_i is bounded between 0.1 and 1.0. The optimization process iteratively adjusts the K_p and K_i values based on particle positions and evaluates their performance using a fitness function. The fitness function aims to minimize the Integral of Absolute Error (IAE) of the DC-link voltage regulation during steady-state ($t \geq 0.3s$), effectively promoting stable and accurate voltage control. During this optimization, data comprising the error signal, its derivative, and the corresponding PI controller output (control signal) are collected for the global best performing particle, alongside fitness values and iteration/particle indices.

Finally, the PSO-optimized PI controller is replaced by an ANN controller to potentially further enhance performance and robustness. The training data generated during the PSO optimization (specifically, the error signal and its derivative as inputs, and the corresponding optimal PI control signal as the target output for the global best parameters) is used to train the ANN. Figure 7 shows the points where input and output data for the ANN are captured from the simulation running with the optimized PI controller.

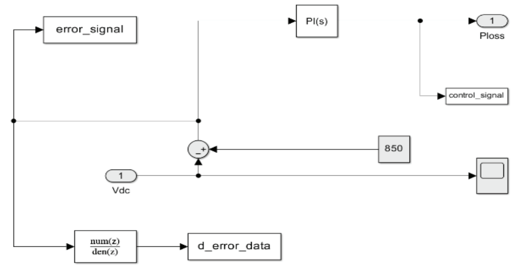

Fig 7: Generating input ($error, d\_error$) and output ($control\_signal$) data for ANN training from the optimized PI controller simulation.

The ANN architecture, consists of an input layer with 2 neurons (for error and derivative of error), a hidden layer with 20 neurons using the hyperbolic tangent (tanh) activation function, and an output layer with 1 neuron using a linear activation function to produce the control signal (P_{loss}). The network is trained using MATLAB's `fitnet` function, which employs the Levenberg-Marquardt algorithm by default, optimizing for Mean Squared Error (MSE) between the ANN output and the target PI controller output. The collected data is divided into training (70%), validation (15%), and testing (15%) sets.

After training for 1000 iterations, the network with the best validation performance is saved. MATLAB's

`gensim` function is used to convert the trained network into a Simulink block. This ANN block then replaces the PI controller block in the V_{dc} regulation loop, as shown in Figure 8. The ANN controller takes the real-time error signal and its derivative as inputs and generates the control signal (P_{loss}) based on the learned relationship from the optimized PI controller's behaviour. This approach aims to achieve stable DC-link voltage regulation comparable or superior to the optimized PI controller, thereby contributing to effective harmonic distortion reduction by the SAPF. The overall control strategy evolves from basic SAPF operation, enhancement via PI control, optimization of PI gains using PSO, and finally replacement with a trained ANN controller leveraging the optimized behaviour.

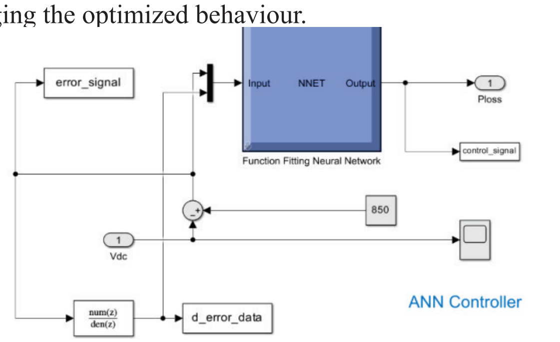

Fig 8: Replacing the PI controller block with the trained ANN controller block in the Simulink model.

III. Results and discussion

A) *Harmonic Analysis in Uncompensated System*

Initially, a simulation was conducted on the system with only the nonlinear load connected, without any compensation. The harmonic analysis of the source current revealed significant distortion, as shown in the FFT analysis presented in Figure 9. The calculated THD was found to be 28.24%. This high baseline value indicates a substantial level of harmonic content injected by the nonlinear load and underscores the necessity for effective mitigation techniques.

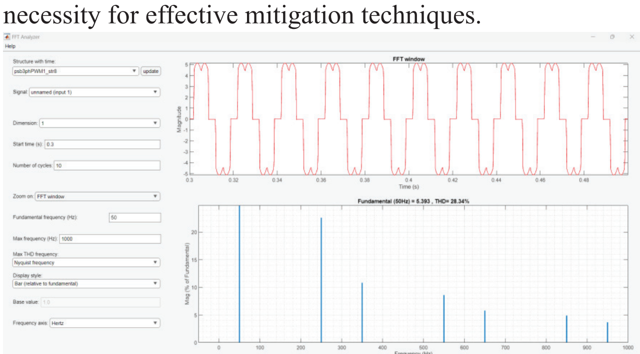

Fig 9: Harmonic analysis (FFT) and THD measurement of the source current with only the nonlinear load (uncompensated system)

B) *Conventional SAPF Implementation*

To address the identified harmonic problem, a conventional Shunt Active Power Filter (SAPF) was implemented. This SAPF utilized the instantaneous power (PQ) theory for reference current generation and employed a hysteresis current controller for switching signal generation. The implementation of this conventional SAPF demonstrated significant improvement in power quality compared to the uncompensated case. As shown by the FFT analysis in Figure 10, the THD of the source current was reduced from the initial 28.24% to 14.01% (measured over 10 cycles), confirming the effectiveness of the basic SAPF topology in mitigating harmonics.

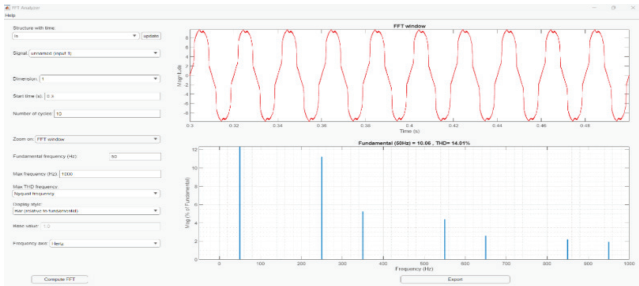

Fig. 10: Harmonic analysis (FFT) and THD measurement of the source current with the conventional SAPF implemented.

C) *PI-Controlled SAPF Enhancement*

Further enhancement was achieved by integrating a Proportional Integral (PI) controller into the SAPF's DC-link voltage regulation loop. This controller helps maintain a stable DC voltage (essential for proper inverter operation) and accounts for the power loss component (Ploss) when generating the reference currents, leading to more accurate compensation. The simulation results for the PI-controlled SAPF, presented in Figure 11, show a substantial additional reduction in harmonic distortion compared to the conventional SAPF. The source current THD decreased significantly further to 3.43% (over 10 cycles).

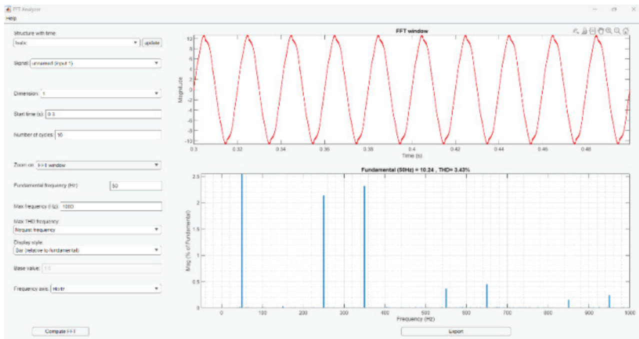

Fig. 11: Harmonic analysis (FFT) and THD measurement of the source current with the PI controller based SAPF.

D) *PSO-Tuned PI-Controlled SAPF Enhancement*

Recognizing that the PI controller's performance is sensitive to its tuning parameters, Particle Swarm Optimization (PSO) was employed to optimize the proportional (K_p) and integral (K_i) gains. The optimization process, described in the methodology, converged to final values of $K_p = 0.5$ and $K_i = 0.12$. Implementing the SAPF with these PSO-tuned PI gains led to improved dynamic response and steady-state performance in the DC voltage regulation, resulting in more effective harmonic compensation. Figure 12 shows the harmonic analysis for this configuration, indicating a further reduction in the source current THD to 1.64% (over 10 cycles), surpassing the performance of the non-optimized PI controller.

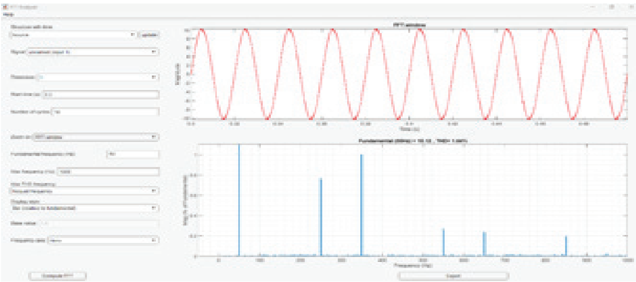

Fig 12: Harmonic analysis (FFT) and THD measurement of the source current with the PSO-tuned PI controller based SAPF ($K_p = 0.5$, $K_i = 0.12$).

E) *ANN-Based SAPF Enhancement*

Finally, the PSO-tuned PI controller was replaced by an Artificial Neural Network (ANN) based controller for DC-link voltage regulation. The ANN was trained offline using data generated by the system operating with the optimized PI controller, effectively learning the optimal control mapping. Implementing this ANN-based control strategy yielded the best harmonic mitigation performance among the tested methods. The corresponding harmonic analysis, shown in Figure 13, demonstrates a further reduction in the source current THD to 1.41% (over 10 cycles), slightly improving upon the PSO-tuned PI controller result.

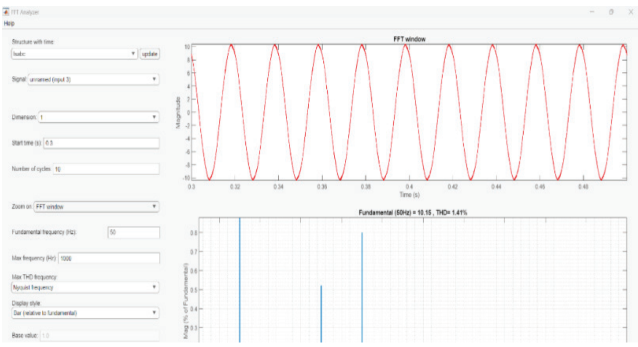

Fig. 13: Harmonic analysis (FFT) and THD measurement of the source current with the ANN controller based SAPF.

IV. DISCUSSION

The progression of THD reduction across these different strategies is summarized visually in the bar chart presented in Figure 14. The results clearly indicate that while the conventional SAPF pro videos substantial harmonic mitigation, the addition of a DC-link voltage controller (PI) significantly improves performance. Furthermore, optimizing the PI controller gains using PSO offers further refinement, and replacing the controller with a trained ANN achieves the lowest THD, demonstrating the potential advantages of intelligent control techniques for enhancing SAPF effectiveness. The final THD of 1.41% achieved with the ANN controller represents a significant improvement from the initial 28.24% in the uncompensated system, bringing the harmonic distortion well within standard limits like those suggested by IEEE 519.

Table 1 Source Current THD Comparison for Different Compensation Strategies.

Strategy/Configuration	THD (%)
Uncompensated System	28.24
Conventional SAPF (PQ + Hysteresis)	14.01
PI-Controlled SAPF	3.43
PSO-Tuned PI SAPF ($K_p = 0.5, K_i = 0.12$)	1.64
ANN-Based SAPF	1.41

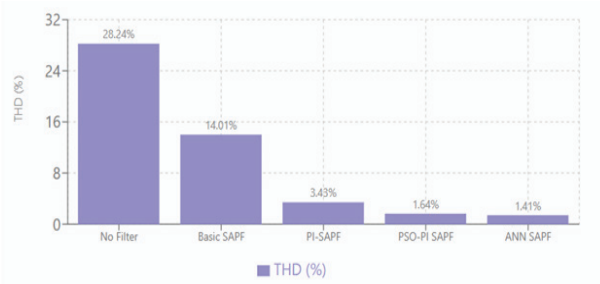

Fig. 14: Comparison of source current THD (%) across the different implemented strategies.

V. Conclusion

Increased use of nonlinear devices is causing harmonics to enter power system networks, which distorts voltage and current signals and damages power distribution infrastructure. Our proposed system shows promising results in the reduction of the Total Harmonic Distortion in these networks. Total Harmonic Distortion (THD) of the system decreased from 28.34% to 1.41% as a result of the progressive implementation of the Shunt Active Power Filter (SAPF), the use of a PI-controller, the optimization of the PI-controller using Particle Swarm Optimization (PSO), and the replacement of the optimized PI-controller with an ANN controller. The source current's Total Harmonic Distortion (THD) is greatly decreased, making the power source cleaner and more reliable. These results demonstrate the ANN-based shunt active power filter's notable reduction in harmonic content.

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