PSO Trained Feed Forward Neural Network Based SAPF for Power Quality Enhancement in Distribution Networks

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***Abstract*—Power distribution infrastructure is being harmed by the advent of nonlinear devices, which cause harmonics to enter into the power system networks and distort the voltage and current signals. Shunt Active Power Filter (SAPF) is a new power electronics-based technology that can reduce harmonics and improve the power quality in distribution networks. This research provides an efficient and inexpensive strategy to minimizing harmonics and improving the power quality in power distribution networks by employing Shunt Active Power Filter's (SAPF), which uses the Particle Swarm Optimized Artificial Neural Network Controller (PSO-ANN). The goal of the PSO-ANN algorithms have been developed for SAPF is to improve system performance by lowering the amount of Total Harmonic Distortion (THD). In this work, the standard PI controller is initially tuned using the PSO algorithm to obtain the optimal gain values (K_i, K_p) for the PI controller. After that, these values of the PSO-PI controller's input and output will serve as a dataset for the ANN controller. Now, the PSO algorithm is being used to tune this ANN controller in order to acquire the optimal values for the weight and bias. Using the MATLAB/SIMULINK tool, the proposed algorithm's performance is evaluated and compared to that of a PSO-PI based SAPF and the conventional PI based SAPF. The results of the simulation demonstrate that a SAPF which is based on a PSO-ANN controller is capable of achieving superior THD in the drawing source current while maintaining minimum levels and which are acceptable in accordance with the IEEE-519 standard for harmonics.**

***Index Terms*—ANN-controller tuning, particle swarm optimization algorithm, PI-controller tuning, power quality, shunt active power filter, total harmonic distortion**

I. Introduction

Harmful harmonic currents are produced at the Point of Common Coupling (PCC) due to the usage power electronics devices and non-linear load in huge quantities [1]. Because of the many issues that can arise from distribution system current harmonics, loss, instability, noises, heating appliances, etc. It would be preferable to reduce their risk and bring them down to an acceptable level, as specified by the IEEE-519 standards for Total Harmonic Distortion (THD) [2].

To reduce current harmonics, compensate for reactive power, and improve power factor, a Shunt Active Power Filter (SAPF) could be the solution. Fig. 1 (next page) depicts the SAPF setup, this consists of the active filter controller as well as the Voltage Source Inverter (VSI). In order to achieve the desired result of injecting a controlled compensating current into the power system, the VSI requires instantaneous adequate firing signals from the control unit [3, 4]. The reactive power control to the grid is supplied by the DC-link capacitor employed on the front side of the VSI [5]. In order to connect the DC component to the three-phase power distribution system, a VSI is necessary. To reduce the amount of distortion in the source current, VSI injects a compensating current in response to the firing signals [6].

To analyze the VSI switching operation, either reference generating methods or control techniques are used. The SAPF control techniques are able to be implemented in two steps, which are as follows: first, by using reference current generation theories to extract compensating signals from distorted signals, and then, by using signal estimated reference methods to produce appropriate firing signals for the purpose of controlling the SAPF switching devices [7]. Several writers have compared SAPF control techniques ([8, 9]).

The PI-controller, which is an integral aspect of reference current theory, is responsible for minimizing the impact of harmonics. K_i and K_p gain settings of the PI-controller need to be properly tuned in order to obtain the best possible results. The traditional approach for tuning the gains of the PI-controller utilizes linear modeling, which ultimately results in a less-than-optimal setting for the gains [10, 11]. Consequently, PI-controller tuning makes use of a variety of different metaheuristic optimization strategies. There are a variety of control methods that can lower current harmonics and introduce the converter to brand new opportunities [12]. Consider, for example, the Particle Swarm Optimization (PSO) [13−17] method and Genetic algorithm (GA) [18].

Artificial Neural Network (ANN) is a network that is set up and works in a way that is similar to how the human brain works. To simply stated, the brain is a network of cells called neurons. The behavior of the

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whole network depends on how strong the connections between interneuron's are and how they are set up. During the training of the network, the weights are changed and tweaked [19]. At the moment, Artificial Neural Network (ANN) techniques are only used on SAPF for producing reference compensation current, which is used to control the compensation that SAPF gives [20, 21]. Learning weights can be accomplished in a variety of techniques [22]. Some examples include the Widrow-Hoff (W-H) approach, the Steepest Descent method of variable learning, the Levenberg-Marquardt method, and others.

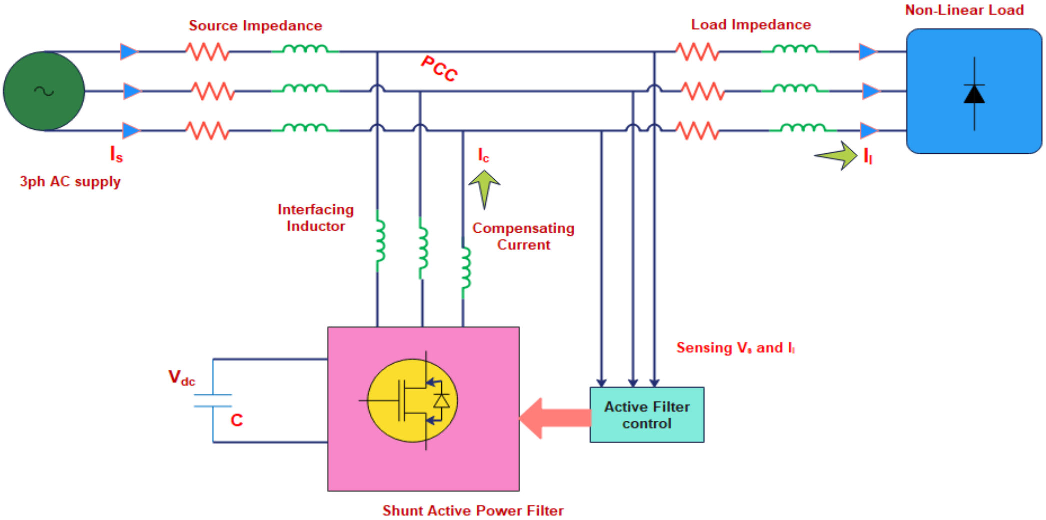

Fig. 1. Basic elements of the shunt active power filter.

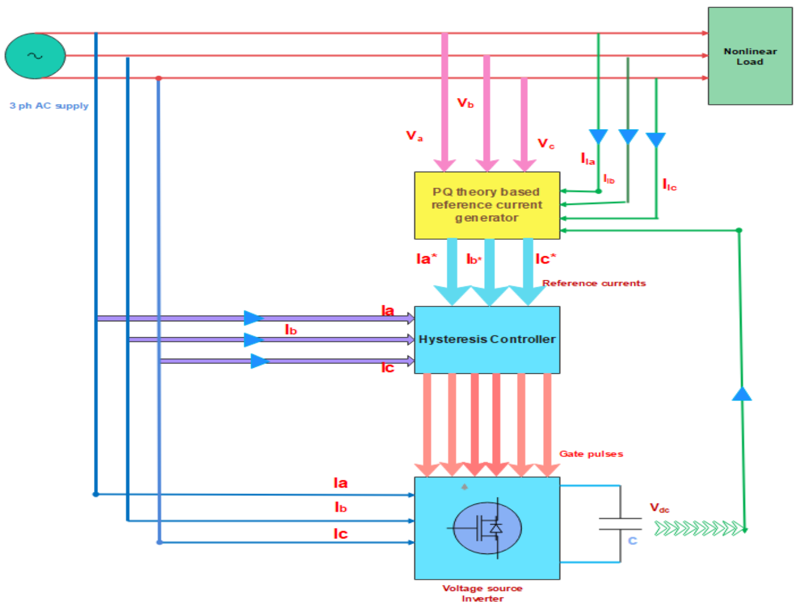

Fig. 2. SAPF controller configuration.

This work uses the concepts of instantaneous active and reactive power to derive the reference current (PQ-theory). Hysteresis current controller technique, as shown in Fig. 2 [23], estimates reference currents to provide necessary gating pulses. For optimum performance of a PQ-theory based ANN-controller for a dc-link voltage requires fine-tuning of weight and bias values. For the optimum ANN-controller weight and bias particle swarm optimization algorithm is implemented in order to identify its optimal state.

II. PQ Theory

In the case of three-phase, three-wire systems that have sinusoidal and balanced source voltages, a PQ-theory-based constant instantaneous power control approach has been developed. The instantaneous power is calculated by sensing the source voltage (V_a, V_b, V_c) and load current (I_{la}, I_{lb}, I_{lc}) and transforming them using Clarke transformation into (α, β) components. Error signal is derived from reference and measured dc-link voltages, then introduced to PI or ANN controller to obtain power losses component of dc-link voltage (P_{loss}). As illustrated in Fig. 3 (next page) [24], the reference current signals are obtained by inverting the components (α, β) with the real and reactive power by use of the inverse Clarke transformation (α, β to three phase values (V_a, V_b, V_c, I_{la}, I_{lb}, I_{lc}).

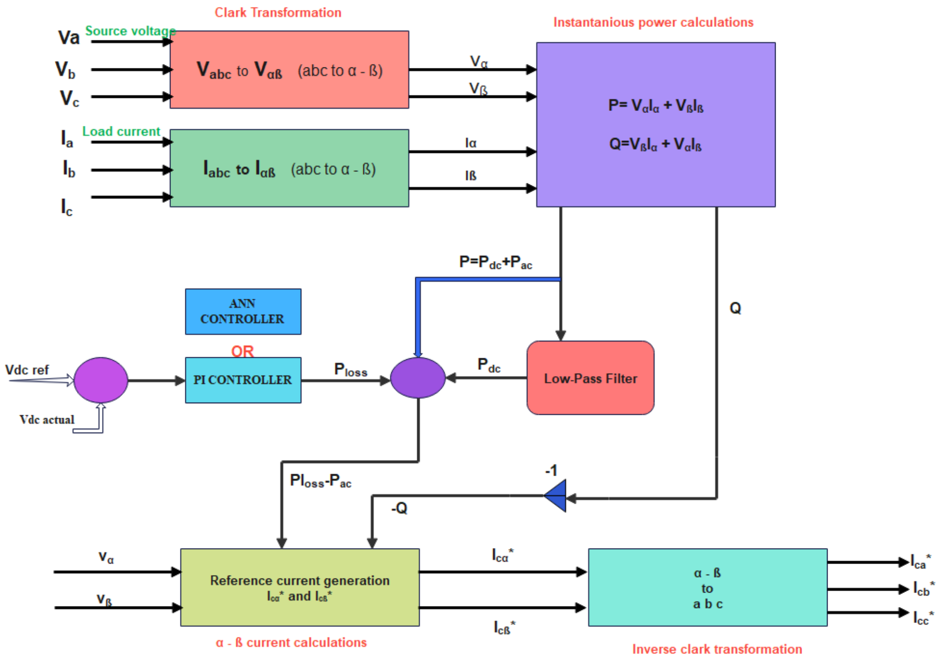

Fig. 3. Work flow of PQ theory based reference current generation.

III. Artificial Neural Network (ANN)

The human brain's structure is built on neural networks, hence the terminology "Artificial Neural Network" is adopted from the neuroscience area. Multiple layers of interactions are present between neurons in artificial neural networks, just like the neurons in the human brain are connected to each other. These nerve cells are called nodes as shown in Fig. 4. A nominal neuron is a processing element that, in general, possesses one or more outputs and n inputs (x_1, x_2,⋯, x_n) which are the independent inputs or outcomes of the different neurons. Fig. 5 provides a visual representation of these inputs and outputs. The neuron begins by computing the sum of its inputs, and then it transfers this value through its activation function in order to form its output, which is indicated by the value Y_i [25].

$$Y_i = f_i\left(\sum_{j=1}^{n} w_{i,j}x_j + b_i\right) \tag{1}$$

where $w_{i,j}$ are the weight of the connection between the input neuron and the output neuron, b_i is the bias of the neuron, x_j represents the neuronal input, and f is activation function that controls the characteristics of the neural network.

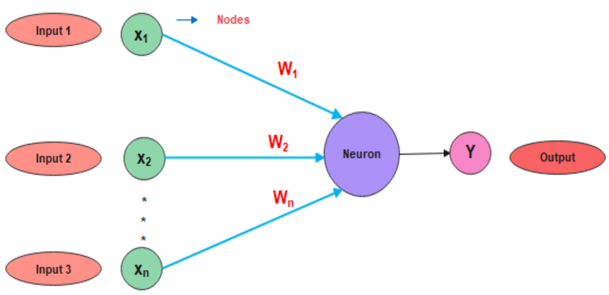

Fig. 4. Basic structure of artificial neural network.

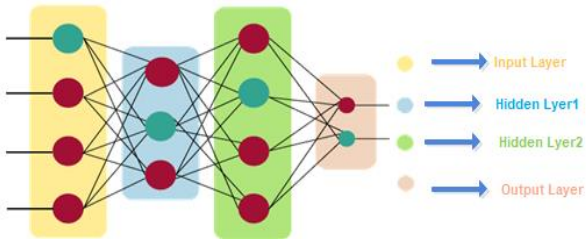

Fig. 5. Architecture of the artificial neural network.

Neural networks adjust to input data by changing connection weights (including biases) and sometimes layer number and neurons number.

IV. Introduction to PSO

The comprehensive implementation of PSO algorithm starts with the movement of a group of possible random solutions, which are represented in the form of moving particles in inside target region. This movement is done in order to find the optimal solution. Every one of the nearby particles that are being assumed has some a speed as well as a selective memory, which enables each other to recall the position and value that corresponds to their optimal level of performance. This is being done by taking into account all of the information that is currently being taken into account. A predetermined objective function that is tied to the problem that needs to be resolved [26] is used to evaluate the efficacy of each individual particle. The velocity of each particle at iteration is determined by linearly combining the velocity and position at iteration, as well as the intervals that separate the existing position of the particle from its preceding best position and finest position, respectively. This information is then used to calculate the velocity of each particle. This leads to the development of a formula for determining the velocity of the particle at the next iteration, which is denoted by t+1. The motion of the particles is formalized for us by Eqs. (2) and (3), which provide us a representation of the movement of the particles.

$$
\begin{aligned}
v_i(t) = wv(t-1) + \\
\left[P_{\text{best}}(t-1) - x_i(t-1)c_1r_1\right] + \\
\left[G_{\text{best}} - x_i(t-1)\right]c_2r_2
\end{aligned}
\tag{2}
$$

$$x_i(t) = x(t-1) + v_i(t) \tag{3}$$

where x_i is the ith particle position, v_i is the ith particle velocity, P_{best} is particle best position, G_{best} is target position, w is coefficient of inertia, c_1 and c_2 are coefficients of acceleration, and r_1 and r_2 are values at random between 0 and 1.

Iterate (2) and (3) until convergence is achieved [27].

V. Proposed Implementation

A. PSO Tuned PI Controller

The primary function of SAPF is dependent on DC link voltage regulation, which is controlled by standard PI controller. This controller requires a great deal of mathematical calculation, and it is possible that it will not produce optimal gain values for k_p and k_i. With the help of the PSO algorithm, we can determine the optimal values for k_p and k_i.

The actual dc voltage as compared to the reference dc voltage and the error that will be fed to the PSO-PI controller can be seen in the Fig. 6. The Integral Absolute Error (IAE) is the objective function that needs to be minimized with the help of the PSO algorithm in order to obtain the optimal gain values. The parameters for the PSO are specified in the Table I.

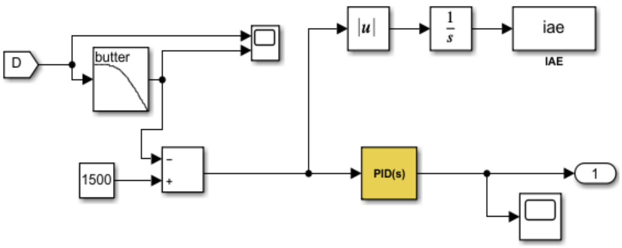

Fig. 6. DC voltage regulation of SAPF with PSO-PI controller.

TABLE I: PSO PARAMETERS

Maximum iterations	1000
Total Population	50
Weight of Inertia	0.89
Constant of Acceleration (C_1)	2
Constant of Acceleration (C_2)	2
Total Variables	2
Higher Limit of K_i, K_p	200
Lower limit of K_i, K_p	0
Optimum value of K_p	5.65119
Optimum value of K_i	7.93019

B. PSO Tuned ANN Controller

The objective of ANN training is to arrive at the most accurate possible values for the network's weights and biases. The right values of the ANN's weights and biases are determined by the application of a variety of methodological approaches. The PSO method was utilized in this paper. According to the Fig. 7, the input (e) and output of the PSO-PI controller will serve as the dataset for the neural network feed forward controller.

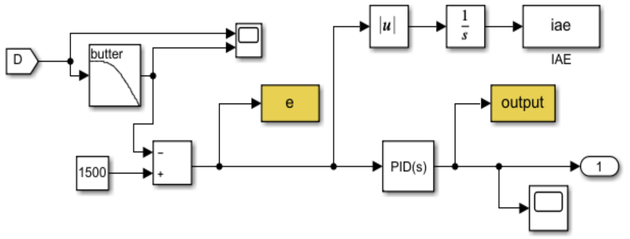

Fig. 7. The workspace representation of the PSO-PI controller's input (e) and output.

The Initialization of the neural network code shown in below says to get the input and target values from the PSO-PI controller, then initialize the hidden neurons are 10, configure the neural network based on the input and output, get the weights and bias of the configured neural network, create the objective function as root mean squire error, and use the PSO algorithm to fine-tune the weights and bias of the pre-trained neural network.

Initialize the neural network problem

- ➢ inputs = e';
- ➢ expects = output';
- ➢ hn = 10; (number of hidden neurons)
- ➢ Nn = feedforwardnet (hn);
- ➢ Nn = configure (Nn, inputs, expects);
- ➢ getwb(Nn) (Getting initial weight and biases)
- ➢ Based on weights and bias(y), Nn, inputs, and expects, calculate the objective function which is root mean square error denoted by (g).
- ➢ Train the neural network by applying the PSO algorithm .From that we can obtain the updated weights, bias (y), and error (e).
- ➢ Nn = setwb(Nn, y');
- ➢ getwb(Nn)
- ➢ e = expects - Nn (inputs);
- ➢ def = mean(e.^2)/mean(var(expects',1));
- ➢ gensim(Nn)

The algorithm's operation can be summed up using the steps as follows:

- Initialization at random of all of the local positions X_i (weights and biases).
- Evaluate the fitness function for each initialized particle, which is provided by (4), then establish the local locations $P_{i\text{-best}}$ and the global positions G_{best}.

$$f = \sum \sqrt{(\text{target} - \text{actual output})^2} \tag{4}$$

- Update all $P_{i\text{-best}}$ local positions
- Assess the current best in the area and the fitness function. If $(f P_{\text{best}}) < f(G_{\text{best}})$ then $G_{\text{best}} = P_{\text{best}}$.
- Using (2) and (3), modify the neural networks' weights and biases.
- The process should end if the stop condition holds true. If not, proceed to Step 2 to display the updated weights and biases.

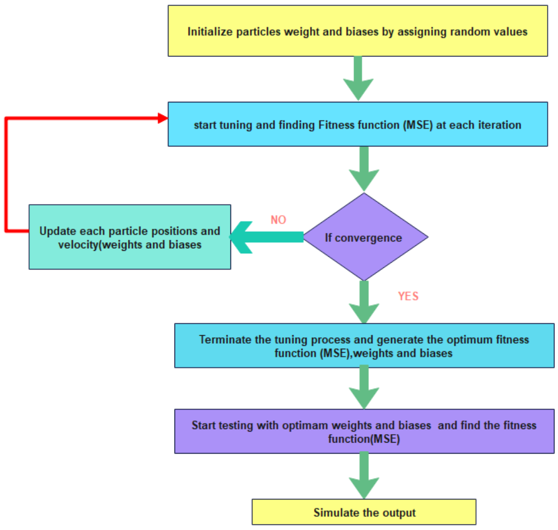

Fig. 8. Flow chart representation of PSO trained ANN controller.

Convergence is reached when the synaptic coefficients settle on a final value and the network's Mean square error (NMSE) drops below a specified threshold. Limiting the number of possible iterations is another way to interrupt the learning process. Fig. 8 depicts the training algorithm's flowchart.

Finally for a given input and an output, we will get the feed-forward neural network as shown in Fig. 9, which will be replaced by the PSO-PI controller.

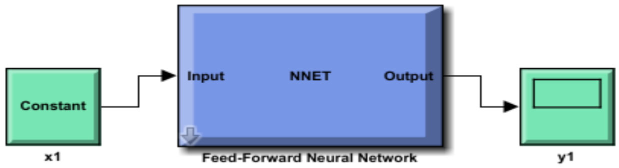

Fig. 9. Simulink block of PSO-ANN algorithm.

TABLE II: SIMULINK MODEL FRAMEWORK

Specification	Values
Source Voltage	415V
Source Frequency	50 Hz
Source Impedance	0.1 ohm, 15mH
Interfacing impedance	15mH
Load Real Power	4472 W
Load Reactive Power	1718 VAR
DC link Capacitance	100μF

VI. MODEL CONFIGURATION

The configuration of the suggested model is shown in Fig. 10, which consists of a three-phase power grid coupled to a three-phase un-controlled diode rectifier coupled to a non-linear load represented by an inductive load on the DC side. SAPF with a VSI design and a capacitor on the DC link are incorporated into the system at the PCC.

The simulation diagram of a PQ theory-based reference control method for SAPF is represented in the Fig. 11. Table II contains a listing of the suggested model's parameters.

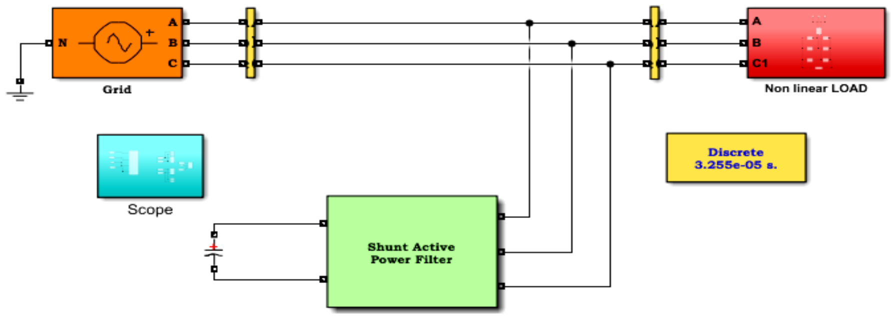

Fig. 10. Simulink model of Grid connected nonlinear load with SAPF.

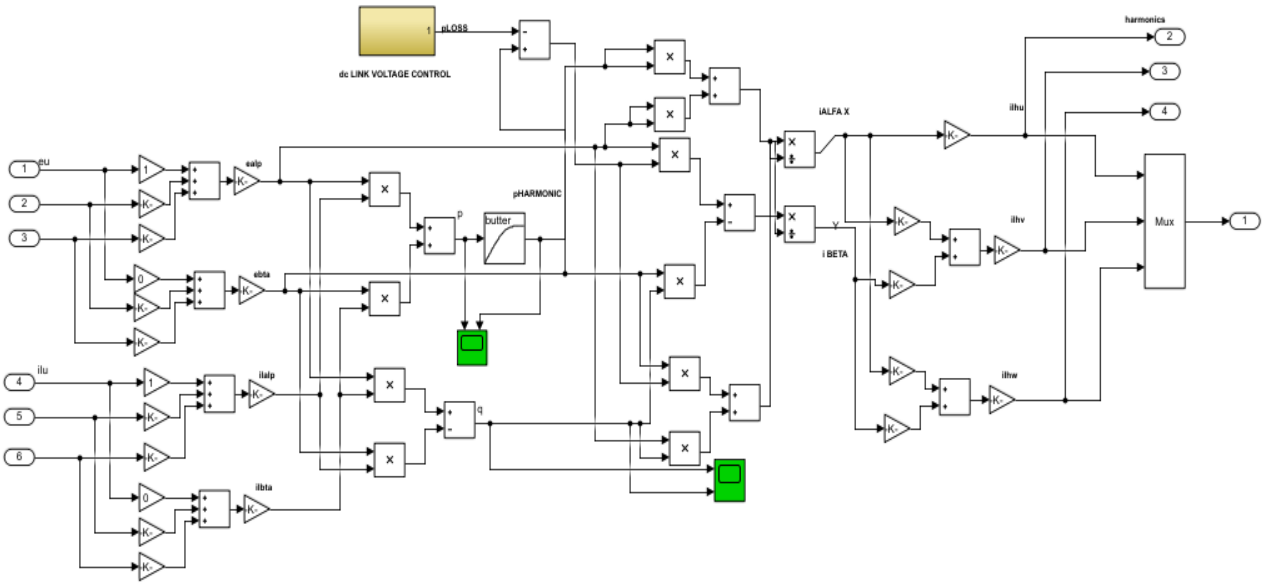

Fig. 11. Simulink model of PQ theory based SAPF.

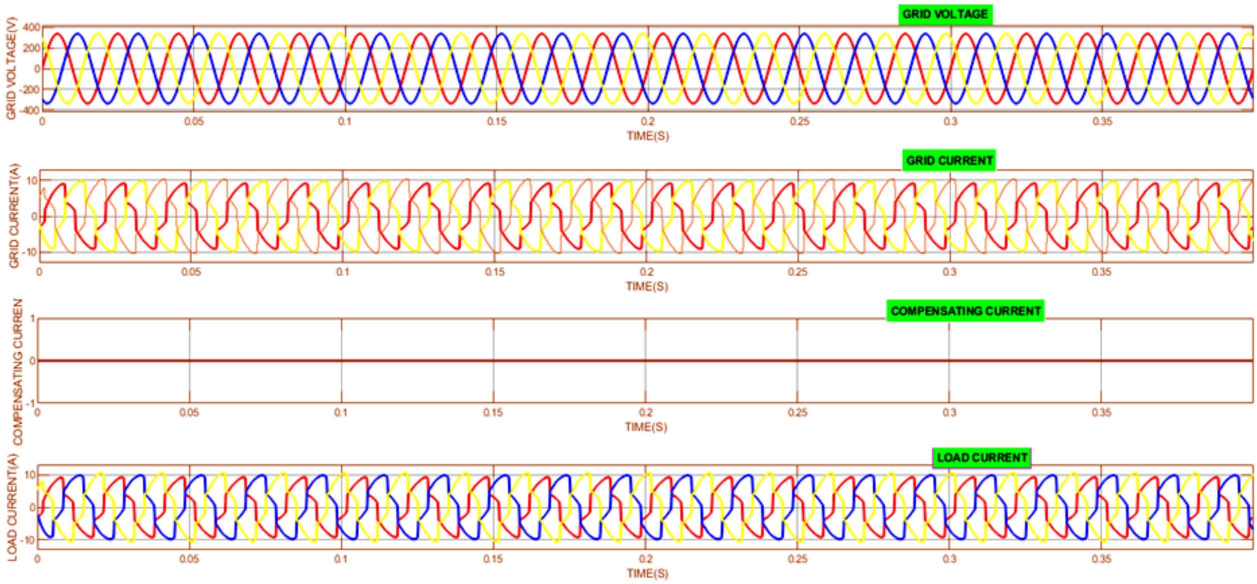

Fig. 12. The source voltage, source current, compensation current, and load current waveforms without SAPF.

VII. Simulation Results

The MATLAB simulative environment was used for the implementation of the proposed reference generation and current control techniques for a SAPF. This research was performed in accordance with the following scenarios.

- Without SAPF
- SAPF with conventional PI controller
- SAPF with PSO-PI controller
- SAPF with PSO-ANN controller

A. Without SAPF

In this scenario, SAPF is switched off, and a distortion in source current induced by a nonlinear load is evaluated using Fast Fourier Transform (FFT) analysis, which came out to be about 18.42%. Fig. 12 shows the source and load current waveforms from the three-phase simulation. Fig. 13 shows the source current FFT harmonic spectrum.

B. SAPF with Conventional PI Controller

In this scenario, SAPF is linked to the PCC, and the results of the simulation are obtained without any adjustment to the PI-controller gains. After SAPF connection, the supply current distortion is brought down to 3.76% of its original value as shown in Fig. 14.

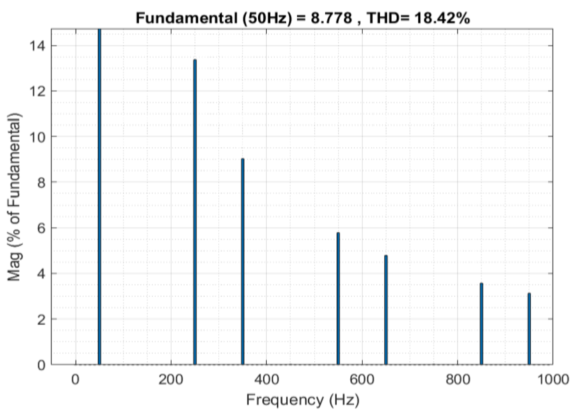

Fig. 13. Grid current THD value of distribution system without SAPF.

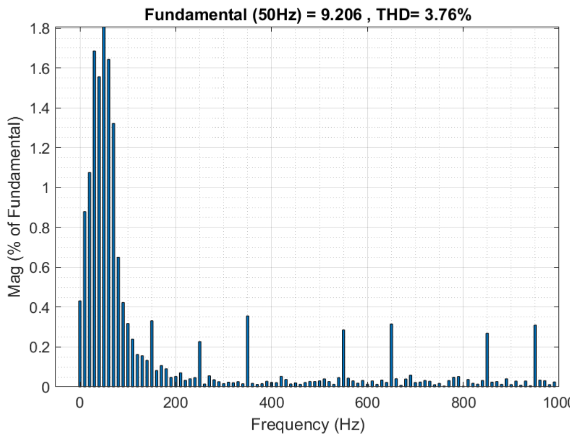

Fig. 14. Grid current THD value of distribution system with PI controller based SAPF.

C. SAPF with PSO-PI Controller

In this particular instance, the simulation was run using the SAPF compensation action, and the PSO Algorithm was utilized to modify the PI-controller gains. The findings that were collected suggest that the THD of the source current has been drastically reduced to 0.93%, as shown in Fig. 15.

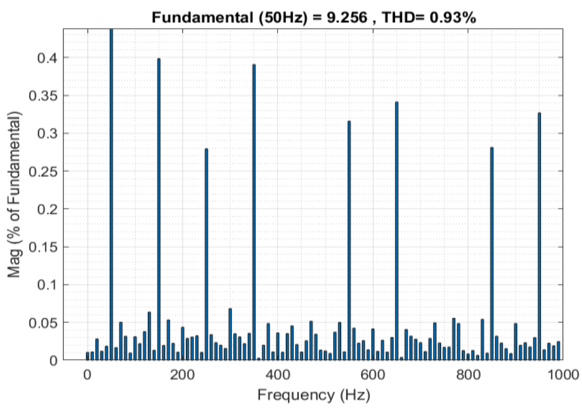

Fig. 15. Grid current THD value of distribution system with PSO-PI controller based SAPF.

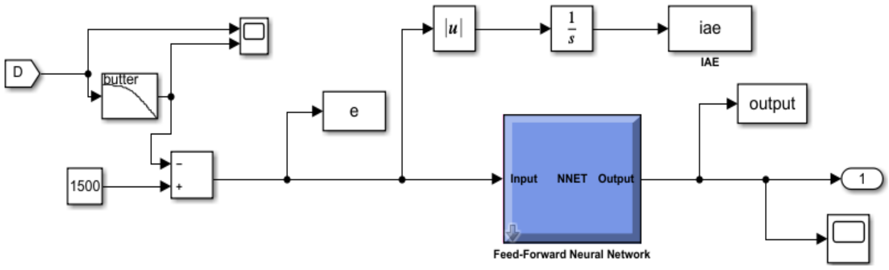

Fig. 16. DC voltage regulation of SAPF by using PSO-ANN controller.

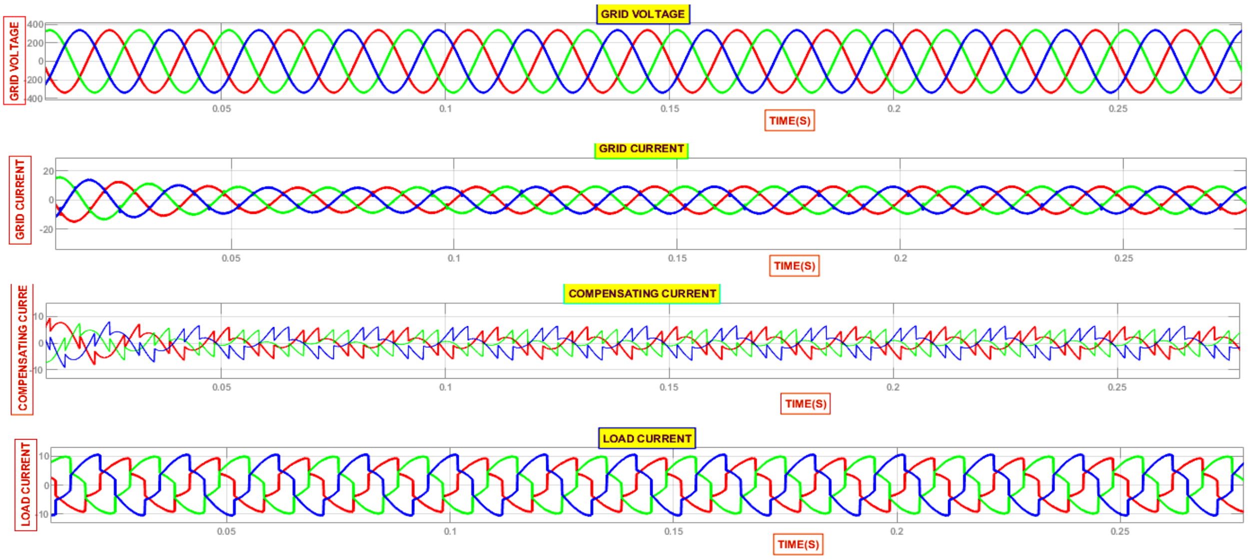

Fig. 17. The source voltage, source current, compensation current, and load current wave forms of PSO-ANN controller based SAPF.

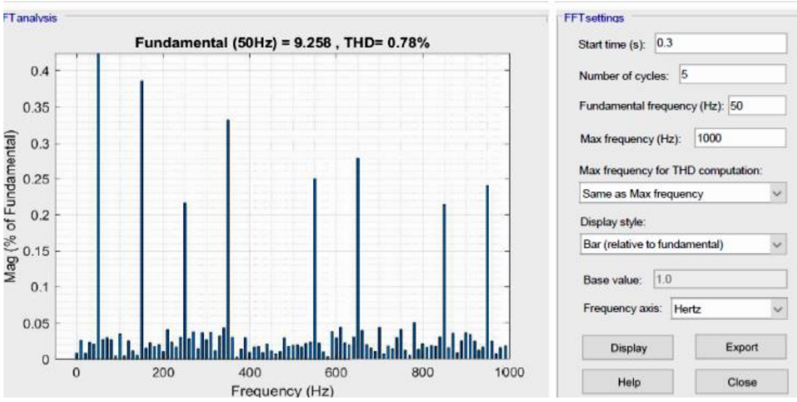

Fig. 18. Grid current THD of distribution system with PSO-ANN controller based SAPF.

D. SAPF with PSO-ANN Controller

In this particular instance, The PSO-PI controller is replaced by PSO-ANN controller Simulink block which was obtained from Fig. 9 Simulink representation with feed forward neural network block as shown in Fig 16. The findings that were collected suggest that the THD of the source current has been drastically reduced to 0.78%.

The source current, load current, and SAPF compensatory current waveforms are depicted in Fig. 17. Fig. 18 depicts the source current's harmonic spectrum. Fig. 19 depicts the converging spectrum for PSO-ANN controller.

PSO-ANN parameters are listed in Table III (next page). The SAPF performances of all four cases are given in Table IV (next page).

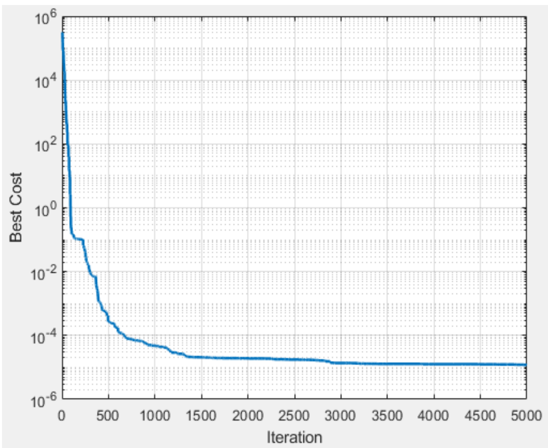

Fig. 19. Converges graph for the PSO-ANN controller.

TABLE III: PSO-ANN PARAMETERS

Maximum iterations	5000
Total Population	50
Weight of Inertia	0.89
Constant of Acceleration(C_1), (C_2)	2
Hidden Neurons	10
Total Variables	1
Higher Limit of weights	200
Lower limit of weights	0

TABLE IV: COMPARISON TABLE

Case studies	FFT -Analysis	Parameters	THD in %
1	Without SAPF	Grid current	18.42
2	SAPF with PI controller	Grid current	3.76
3	SAPF with PSO-PI controller	Grid current	0.93
4	SAPF with PSO-ANN controller	Grid current	0.78

The SAPF performance interns of power factor for all four scenarios as follows: Without SAPF, the power factor is 0.81, with conventional PI being 0.89, with PSO-PI being 0.94, and with proposed PSO-ANN being 0.96.

VIII. CONCLUSION AND FUTURE WORK

The power quality issues, such as harmonics and reactive power, are always expanding and becoming more complex. It has been discovered that implementing strategies derived from artificial intelligence on active filters can produce excellent results in the reduction of harmonics and the correction of reactive power. In this article, the PSO-ANN control method is proposed for use with the SAPF in order to lower the amount of total harmonic distortion occurring on the source side of the distribution system. The SAPF’s effectiveness in a wide range of situations is studied and contrasted. The tool MATLAB/SIMULINK is used to perform simulations of four distinct scenarios, and the findings are reported. According to the results of simulations, both the PSO-PI-based SAPF and the traditional PI-based SAPF perform effective in terms of minimizing THD. It has been found that the proposed ANN-PSO-based SAPF is more effective in simulation in terms of achieving a lower THD value. This improved performance has been determined to be acceptable (within 5% of the IEEE standard), according to the findings of the investigation.

In future work, a hardware-in-loop implementation will be added to the proposed shunt active filter. Also, an ANFIS controller with PSO and other optimization methods will be used to make the SAPF's response even better.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Venkata Anjani Kumar G. was responsible for the development of the theoretical formalism, the working out of analytical calculations, and the performance of numerical simulations. Venkata Anjani Kumar G. is responsible for the final draught of the manuscript and M. Damodar Reddy acted as the project's supervisor throughout its entirety.

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