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TLBO-trained ANN-based Shunt Active Power Filter for Mitigation of Current Harmonics

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Abstract: The increased utilization of nonlinear devices is resulting in damage to power distribution infrastructure by introducing harmonics into power system networks, which in turn causes distortion in voltage and current signals. A novel solution called Shunt Active Power Filter (SAPF) has been developed to address this issue using power electronics. This study aims to provide a method that is efficient and cost-effective for lowering harmonics and improving power quality in distribution infrastructure. The proposed method combines the Teaching learning-based optimization (TLBO) technique with an Artificial Neural Network Controller (TLBO-ANN) in conjunction with SAPF. The primary objective of the TLBO-ANN algorithms in SAPF is to minimise total harmonic distortion (THD) for maximum system efficiency. Initially, Gain values (K_i, K_p) for a regular Proportional-Integral controller are optimised with the Particle Swarm Optimisation (PSO) technique. Those optimized parameters obtained from the PSO-tuned PI controller serve as input and target datasets for training the ANN controller. Subsequently, the TLBO algorithm is utilized to further refine the ANN controller by finding the optimal weight and bias values. Using MATLAB/SIMULINK software, we compare the performance of the proposed algorithm to that of the PSO-tuned PI controller and traditional PI controller. The findings from the simulation suggest that a SAPF utilizing a TLBO-trained ANN controller could improve THD in the supplying current while maintaining harmonics within IEEE-519 accepting levels.

Introduction

Bonding An imbalance between the quality of power available and the power needed by the load apparatus indicates a power quality issue. In order to protect electronic components from power outages, many power enhancement devices have been developed over time (Vishwakarma, 2020). These can be anything from specifically designed power sources to power conditioning devices. Isolation transformers and power conditioning equipment include capacitors, filters, voltage regulators, and uninterruptible sources of power (UPS) to prevent power outages caused by lightning and power surges. Surge capacitors for transient voltage are another type of power conditioning equipment. The Shunt Active Power Filter (SAPF) (Rajeshwari et al., 2017) is an example of a device that enhances power quality. There are many potential sources of damage in alternating current (AC) supply systems. Natural causes include lightning strikes, flashovers, equipment breakdowns and faults, whereas voltage distortions and notches are examples of human-made factors. Because it acts as a nonlinear load and develops non-sinusoidal current, much of the customer's equipment contributes to pollution in the supply system. Power quality is measured in terms of these factors because of the potential for damage to electronic devices due to fluctuations in

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voltage, current, or frequency. Power quality problems can often be traced back to the voltage at the point of common coupling (PCC), where numerous loads are connected (Gowtham et al., 2016; Dorigo et al., 1999; Janga et al., 2020; Huaisheng et al., 2012) Some examples of such problems are harmonics in the voltage, surges of electricity spikes, notches, and sag/dip/swell/imbalance/fluctuations/glitches/flickers/outages.

Non-linear loads, such as heaters, UPSs and variable-speed motors, can place a burden on the power grid and cause outages and other problems in the supply system. Some nonlinear loads can cause power quality concerns by drawing excessive current from the AC mains, creating the low power factor, harmonic currents, reactive power stress, imbalanced currents, and an excess neutral current in three-phase systems are all caused by the unbalancing and harmonic currents that come from using certain non-linear loads. Problems with dielectric breakdown, communication system interference, breaker issues, incorrect measurement, negative sequence currents in rotating electrical machines (especially rotors overheating) and disturbances affecting motor control units and technological control devices., and many others can all contribute to poor power quality (Sabarimuthu et al., 2021).

In some loads, however, the current changes in a way that is out of proportion with the voltage changes that occur at each half-cycle. Non-linear loads refer to this category of conditions. These non-linear loads produce the current and voltage harmonics. Many issues that utilities and power supply organizations face, such as low power factor, inefficient consumption of energy, and voltage fluctuations in the power system, can be traced back to non-sinusoidal current. A perfect compensator is necessary to prevent the harm caused by harmonics (Soliman et al., 2022). Over time, many different types of power enhancement devices have been developed to shield electronics from the consequences of grid failures. Methods that are both effective and efficient include those that are listed below. Implementing power conditioners and substitute energy sources. Power conditioning equipment includes isolation transformers, lightning arrestors, surge capacitors, filters, voltage regulators and an uninterruptible power supply. (Mikkili S et al., 2012; Om P et al., 2016). A Shunt Active Power Filter (SAPF) is one power conditioning device that enhances the supplied electricity's quality. By synchronizing the source current and voltage, current harmonics on the alternating current (Grid) side are cancelled out, and the DC link voltage is maintained at a constant level (Chelli et al., 2015). In order to achieve this goal, the real power flow in the system as well as the there must be no fluctuation in the amount of reactive power flowing into or out of the source.

The SAPF can be controlled by a single controller or multiple controllers working together to maintain a constant DC voltage. This is accomplished by balancing the real power flow in the system with the reactive power flow that comes from or towards the source, which brings the source current in phase with the source voltage (Babu et al., 2020). This cancels out current harmonics on the AC side. SAPF is necessary to eliminate current harmonics. The fundamental compensation principle of the active power filter is depicted in Figure 1. This principle serves as a form of energy storage to provide the real power difference between the load and the source throughout the transient period. When the load state changes, it affects the system's actual power; when that happens, the system will automatically. When compared to the reference voltage, the value of the voltage that is measured across the DC link capacitor is found to be different (Diab et al., 2019; Diab et al., 2018; Wen-guan Wang et al., 2012; Vadi et al., 2021) which leads to the dysfunction of the system. The reduction of the real power disturbance by using different controllers including chicken swarm optimization (Ramesh et al., 2023; Venkata and Reddy, 2023) at the DC link capacitor.

In this study, the utilization of IRP principles is employed to establish the desired current reference (referred to as PQ-theory). The hysteresis current controller technique estimates the reference currents to generate the required gating pulses (Kazemzadeh et al., 2014). Achieving optimal performance of an artificial neural network (ANN)-controller (Tekwani et al., 2020) based on PQ theory for a direct current (dc) link voltage necessitates precise adjustment of weight and bias values (Wilamowski et al., 2010). To determine the optimal state of the ANN controller, a Teaching learning-based optimization (TLBO) (Satapathy et al., 2013) algorithm is implemented, enabling the fine-tuning of weight and bias values.

PQ-Theory-based Reference Current Generation

PQ theory-based constant instantaneous power control is for 3-phase, 3-wire power distribution systems with sinusoidal and symmetrical source voltages. To apply this theory, the three-phase source voltage (V_a, V_b, V_c) and load current (I_{la}, I_{lb}, I_{lc}) must be sensed and transformed by the Clarke transformation into the (α, β) components.

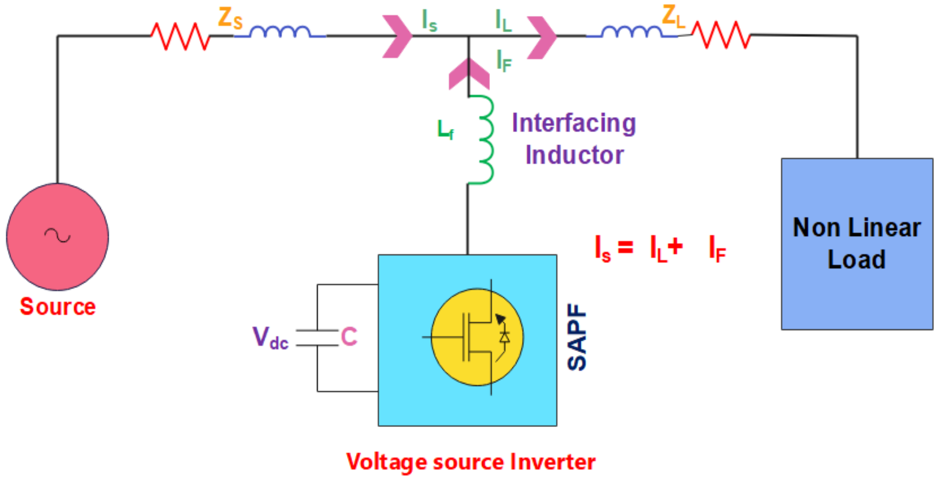

Figure 1. Schematic diagram of a Shunt Active Power Filter (SAPF).

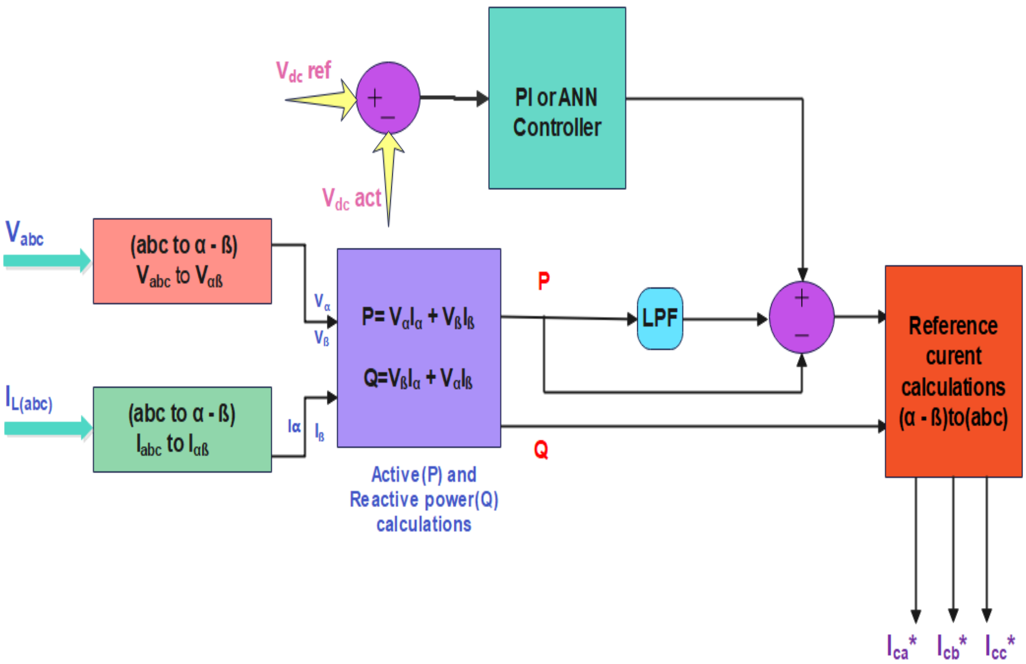

Figure 2. Reference generation diagram with PQ theory.

These components are input for instantaneous power calculations (Akagi et al., 2017). An error signal from the reference and measured dc-link voltages determines the power losses component. A PI controller receives this error signal to calculate power losses (Ploss). The (α, β) components, active and reactive powers, and current calculation are used to estimate the reference (α, β) components. An inverted Clarke transformation transforms these components to 3 phase abc values (I_{abc}, V_{abc}) as shown in Figure 2, to obtain the desired reference current signals.

Artificial Neural Network

An "Artificial Neural Network" is a system inspired by the way the human brain works, which is composed of interconnected neural networks Similar to the human brain. Multiple layers of neurons that are coupled to one another constitute artificial neural networks. These neurons, represented as nodes in Figure 3, are responsible for processing information. Typically, a neuron will have a single or multiple outputs and n inputs (x1, x2,... xn) that will receive or send information to other neurons in the network. In equation 1, the neuron's output, denoted by Yi (Asadi et al., 2022), is the result of multiplying the sum of its inputs by the activation function.

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

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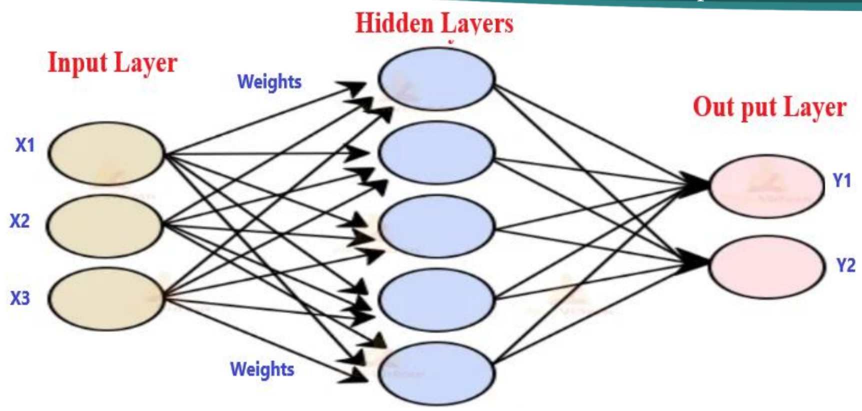

Figure 3. The fundamental structure of an artificial neural network

The $w_{i,j}$ notation represents the connection weight between a neuron on the input and a neuron at target. while b_i represents the neuron's bias. The input to the neuron is represented by x_j and the activation function f determines the neural network's actions. By changing the weights and biases and, in some cases, the number of layers and neurons, neural networks can adapt to new data.

Introduction to TLBO algorithm

Teaching-learning-based optimization, frequently referred to as TLBO, is an acronym given to one of the population-based algorithms that was recently proposed. In the year 2011, Rao et al. presented the teaching learning-based optimization (TLBO) method (Rao et al., 2011). It was inspired by the teaching and learning phenomenon that takes place in a classroom (Rao et al., 2012). In the context of the population-based algorithm TLBO, the class is considered as a population, and each individual learner within the class is considered as an individual member of this population. It is intended that the students in the class will have a greater level of knowledge by the end of the lesson to fulfill this objective. The process has two stages, known as the "teacher phase" and the "learner phase," respectively. This serves as the foundation for achieving this goal.

A. Teacher phase

The student who presents the most outstanding solution in the class is chosen as the teacher. The teacher is regarded as the most proficient learner among the entire population, possessing extensive knowledge and experience in a particular subject. As a result, other students enhance their understanding by leveraging the expertise of the teacher. If a student provides a superior solution compared to the teacher, they will replace the teacher's role. In the kth iteration, the knowledge of the ith learner is updated using the following equation 2.

$$X_i^{new} = X_i + r_I(X_T - T_F{}^i . X_{mean}) \tag{2}$$

In the above scenario, knowledge of the teacher refers to "X_T,","r_I"is a random two-digit number between zero and one, mean results of the learners refers to "X_{mean}," and teaching factor refers to $T_F{}^i$ which can be obtained by the following equation 3.

$$T_F{}^i = round\ [1 + rannd(0{,}1)] \tag{3}$$

At the end of the teacher phase, all of the learners' knowledge is updated, and these values are now ready to be used as input values in the learner phase.

B. Learner phase

When students are in a real classroom, they can learn more by talking to the other students. This is what the TLBO learner phase is built on. During this step, the knowledge of the ith student is compared to that of a randomly chosen jth student as given in equation 4. When students are in a real classroom, they can learn more by talking to the other students. This is what the TLBO learner phase is built on. During this step, the knowledge of the ith student is compared to that of a randomly chosen jth student as given in equation 5.

$$\text{If } f(X_i) < f(X_j) \quad then, \quad X_i^{new} = X_i + r_I(X_i - X_j) \tag{4}$$

$$\text{If } f(X_i) > f(X_j) \quad then, \quad X_i^{new} = X_i + r_I(X_j - X_i) \tag{5}$$

If the knowledge of the **jth** student is better at the end of the learner phase, the knowledge of the **ith** student can be improved as given in equation 6.

$$\text{If } f(X_i^{new}) < f(X_i)\ than,\ X_i = X_i^{new} \tag{6}$$

The TLBO algorithm, consisting of the teacher and learner phases, will continue until either the termination condition or the maximum number of iterations has been reached.

Proposed Methodology

PI controller tuned by PSO

For SAPF, a particularly important role depends on the abilities of a standard PI controller to regulate the DC link voltage. This controller probably produces for kp and ki will not be optimal values. Because it needs a great degree of mathematical calculation, The PSO method can be used to determine the best possible values for both kp and ki.

As shown in Figure 4, the PSO-PI controller will be given an error signal based on the difference between the actual and reference DC voltages. The PSO method must minimize the Integral Absolute Error (IAE) objective function to acquire the ideal gain values. With 1000 maximum number of iterations and 50 Populations, the Optimum values of gains (K_i, K_p) are 5.65119 and 7.93019 (Venkata et al., 2023).

The necessary code to set up the neural network is provided below. The PSO-PI controller's input and target values are retrieved, hidden neurons are initialised. This data is used to configure the ANN, and finally, the network's weights and biases are extracted. Then, we'll define a pre-trained neural network's weights and bias using the TLBO algorithm, with the objective function defined as the root mean square error.

Step by Step approach of TLBO trained ANN

Step1: Take the input (e) from the workspace of PSO-PI controller.

Step 2: Take the Target (output) from the workspace of PSO-PI controller.

Step 3: Assign the number of Hidden Neurons.

Step 4: Define the Feed Forward Neural network based on hidden Neurons.

Step 5: Set up the Neural Network with the specified input and output values..

Step 6: Generate the initial weight and biases

Step 7: Use the root-mean-square-error as the objective function, by utilizing the weights and bias, Feed Forward Neural network, inputs and target values.

Step 8: The neural network is trained using the TLBO algorithm, resulting in the updated weights, biases and error.

Step 9: With this updated weights and biases again

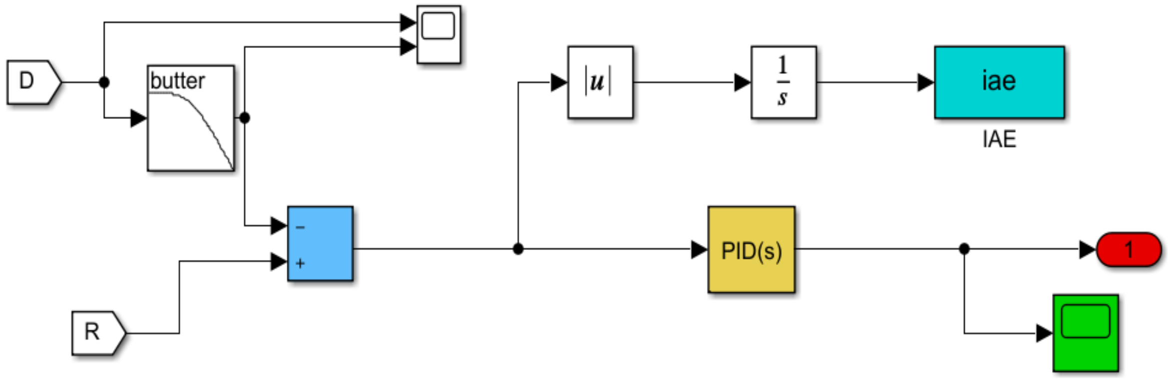

Figure 4. DC link voltage regulation by PSO trained PI based SAPF

TLBO trained ANN Controller

The main objective of a Neural Network algorithm is to obtain the appropriate weights and biases of the network to be as accurate as possible. ANN's weights and biases are given the right values using various methodological approaches. This paper used a method called TLBO. Figure 5 shows that the inputs (e) and outputs (out) of the PSO-PI controller are going to be used as a source of data for the neural network controller.

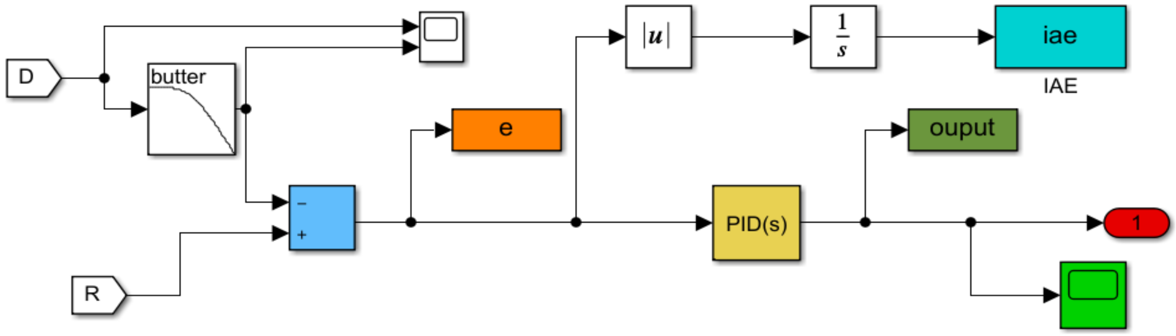

Figure 5. Output (o) and input (e) representation in the workspace for the PSO-PI controller.

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configure the Feed Forward Neural network.

Step 10: Repeat steps 7 to 9 until objective function is at a minimum.

Synaptic coefficients converge when they have settled on steady-state value and the network's Root Mean Square Error (NMSE) decreases below a predetermined threshold. Another approach to stop the learning process is to set a limit on the maximum number of iterations. The flowchart of the training algorithm is illustrated in Figure 6.

We will ultimately obtain the feed-forward neural network block and inside layering structure shown in Figure 7 response to a given input and output. The PSO-PI controller will substitute this feed-forward neural network block.

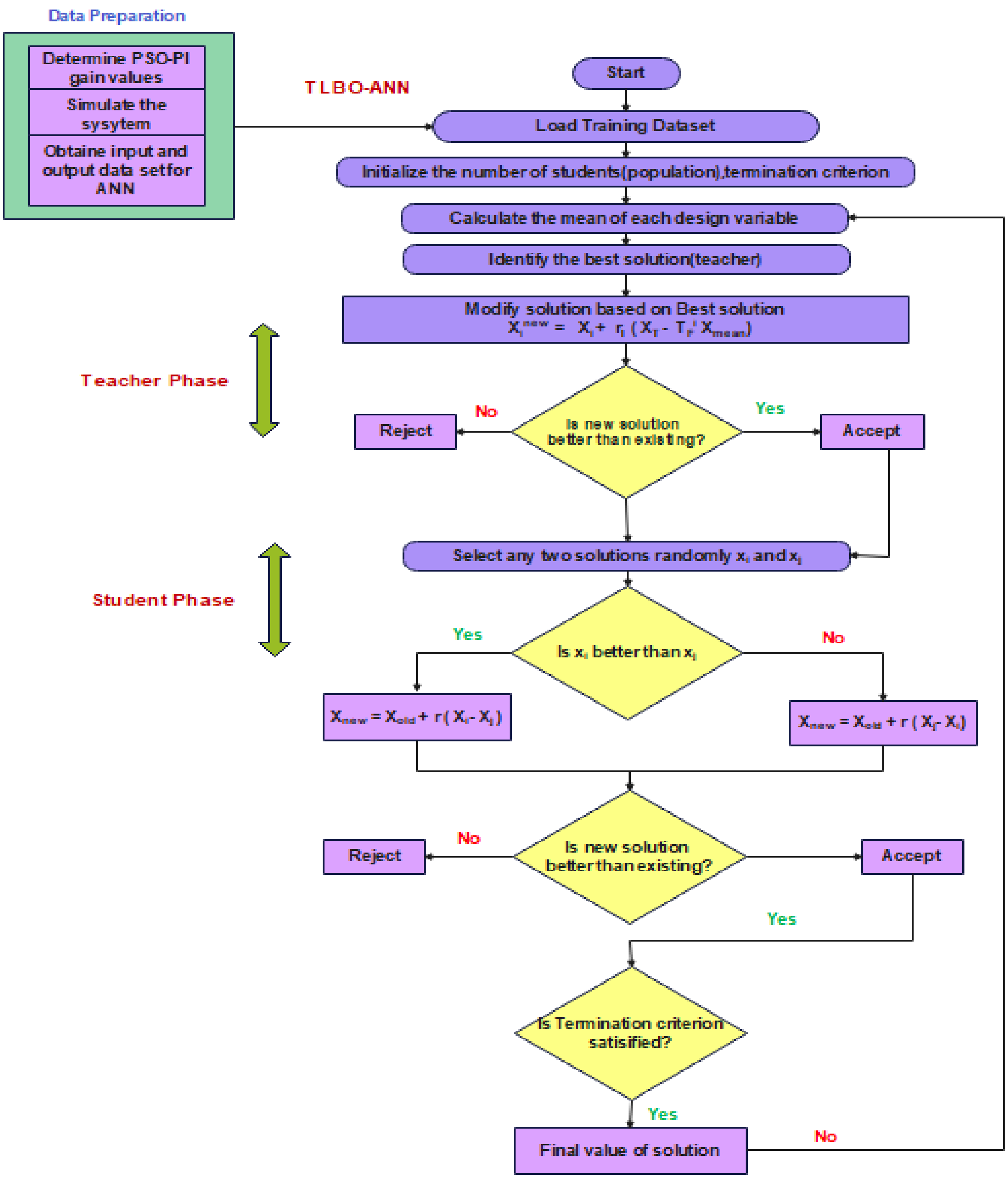

Figure 6. Flow chart of TLBO-ANN.

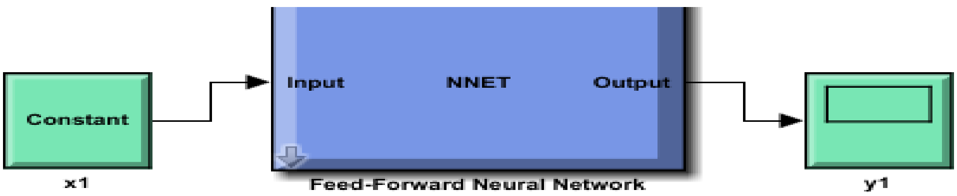

Figure 7. Simulink block of TLBO-ANN algorithm.

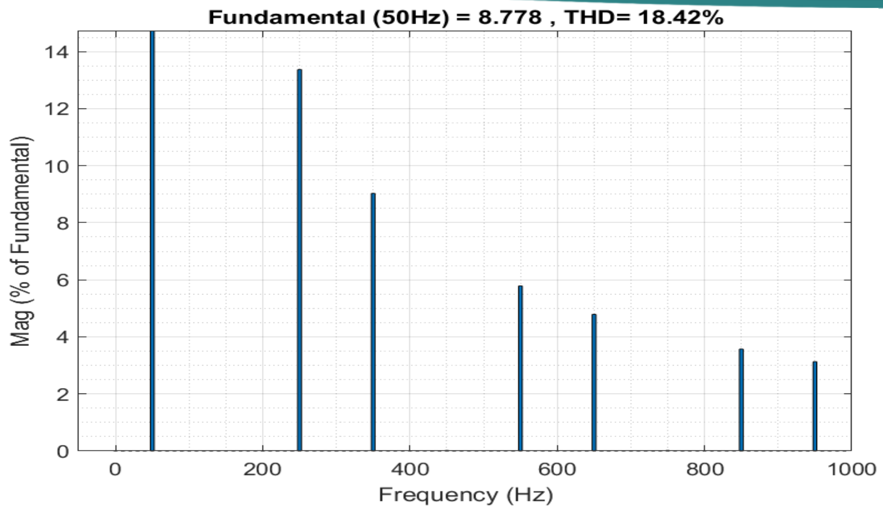

Figure 8. THD result of source current without using SAPF.

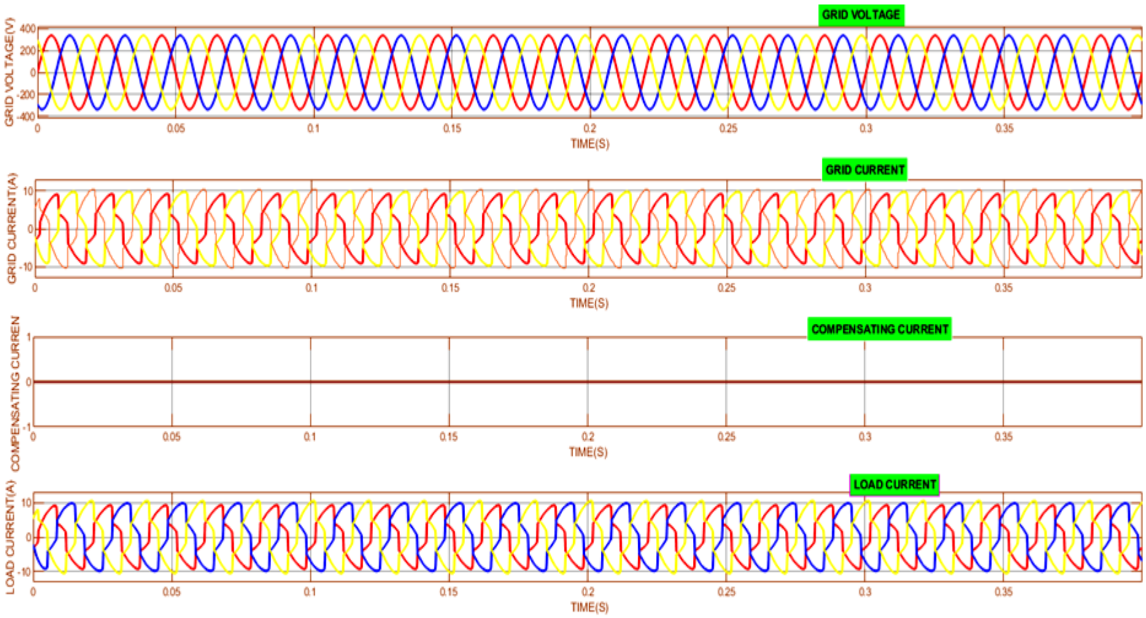

Figure 9. The waveforms of the IL, IS, IC and IS, without using SAPF.

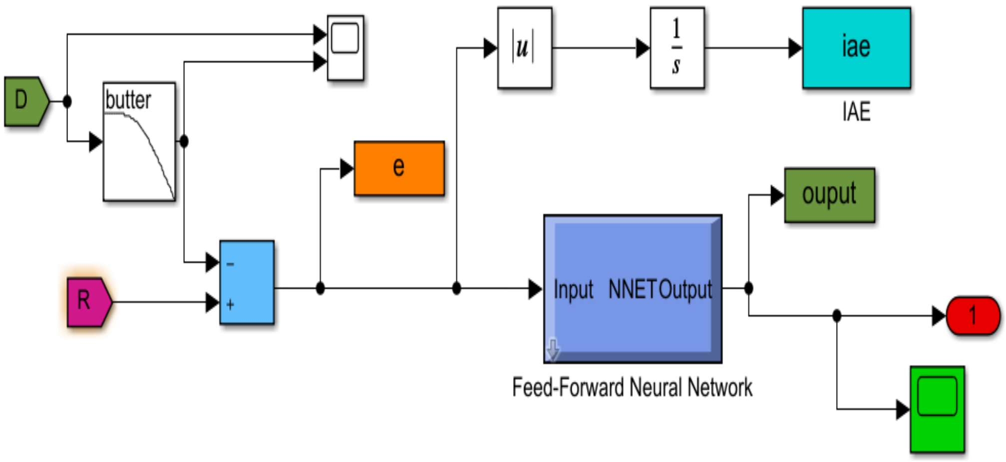

Figure 10. Controlling the DC voltage in a SAPF with a TLBO-ANN regulator.

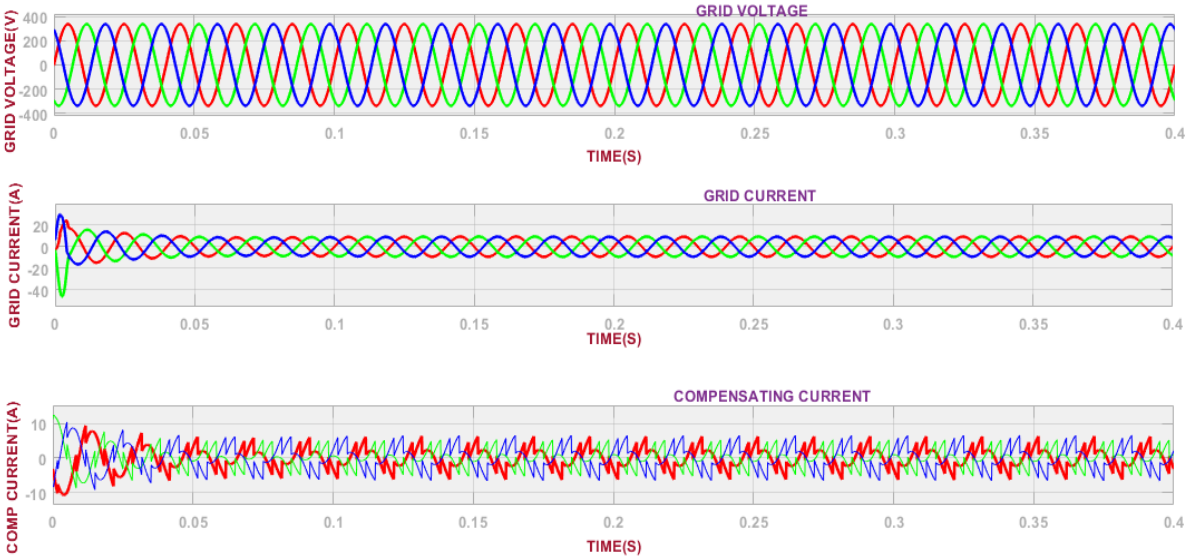

Figure 11. The waveforms of the IL, IS, IC and IS, by using TLBO trained ANN based SAPF

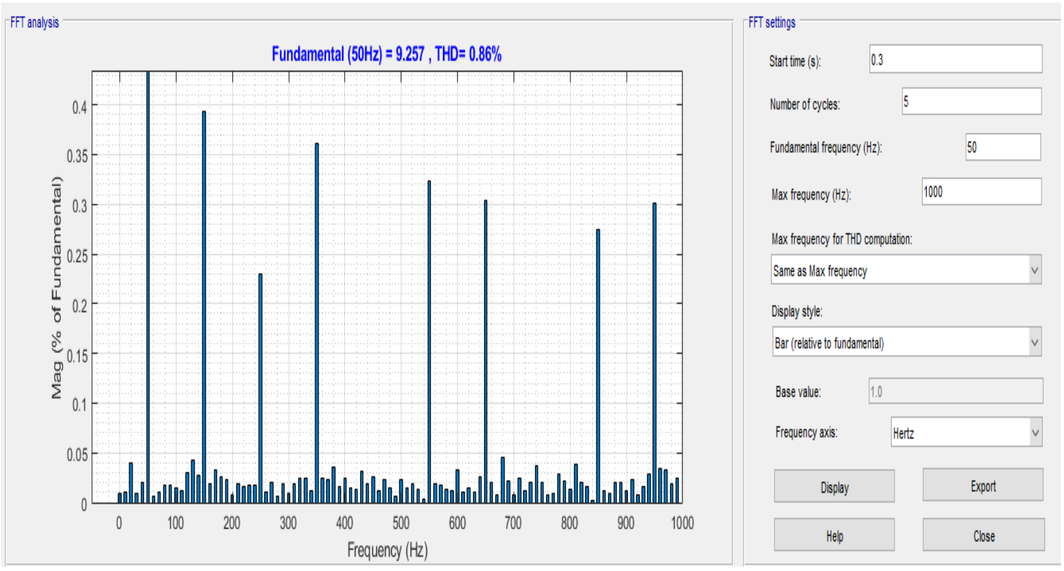

Figure 12. THD result of IS (Grid current) by TLBO tuned ANN-based SAPF.

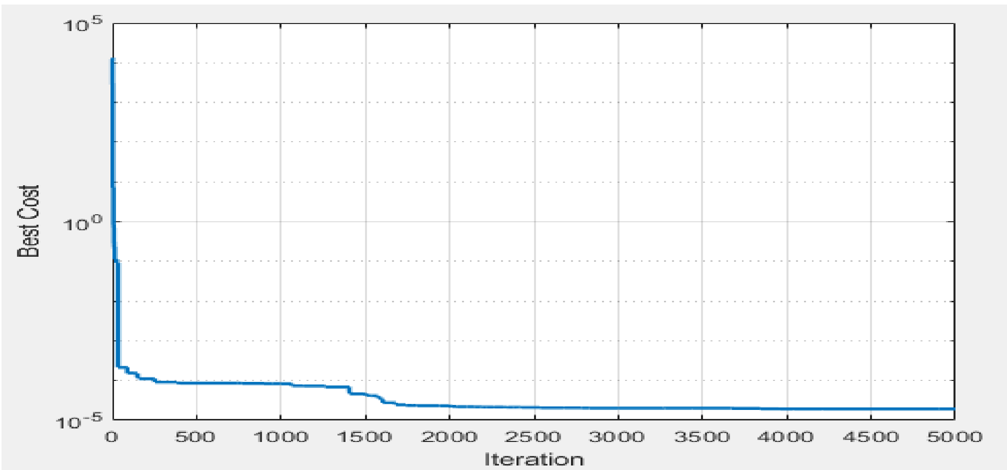

Figure 13. Converges graph for the TLBO-ANN based SAPF.

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Results and discussions

The proposed methods for a SAPF's current control and reference generation were implemented with the help of the MATLAB simulative environment. This study was carried out taking into account the various possibilities that were presented below. A tabulation of the simulation's parameters that were used for the simulation's purposes can be found in Table 1.

Table 1. Modeling framework in Simulink

Particulars	Values
Voltage at the Grid	415V
Frequency at the Grid	50 Hz
Impedance at the Source	0.15 ohm,15mH
Coupling inductance	15mH
Active Power at the Load	4472 W
Reactive Power at the Load	1718 VAR
Connected DC Capacitance	100µF

Without SAPF

In this case, we turn off SAPF and use Fast Fourier Transform (FFT) analysis to look at how the nonlinear load distorts the source current. This analysis showed that the distortion was close to 18.42%. The harmonic spectrum of the source current, as calculated by the fast Fourier transform, is shown in Figure 8. Figure 9 shows the waveforms of the I_S (Grid current), I_L (load current) that resulted from the simulation. The SAPF converter is not injecting a compensating current to reduce grid-side harmonics, as shown in Figure 9.

TLBO-trained ANN-based SAPF

Here, the TLBO-ANN controller Simulink block has taken the place of the PSO-PI controller. This Simulink block was taken from Figure 7 and is shown interacting with a feed-forward neural network in Figure 10. According to the results, the source current's total harmonic distortion (THD) appears to have dropped to 0.86%.

Table 2. Parameters of TLBO-trained ANN

Maximum iterations	5000
Total no of Students	25
Teaching Factor	0.5
Hidden Neurons	10
No of Variables	1
Weight Scale Upper Limits	200
Weight Scale Lower Limits	0

Figure 11 illustrates the waveforms of the currents flowing from the source, the load, and the SAPF compensating current. The harmonic spectrum of the source current is depicted in Figure 12. The TLBO-ANN controller's converging spectrum can be seen as depicted in Figure 13. This indicates that the MSE is steadily reducing and eventually reaching a constant value.

The parameters for the TLBO-ANN are detailed in Table II (on the following page). Table III (on the following page) provides an overview of how the SAPF performed in each of the four scenarios.

Table 3. Table of Comparison

Slno	Type of Controller	Component	THD value(%)
1	Without using SAPF	I_S (Source Current)	18.42
2	PI based SAPF	I_S (Source Current	3.76
3	PSO tuned PI Based SAPF	I_S (Source Current	0.93
4	TLBO tuned ANN based SAPF	I_S (Source Current	0.86

Conclusion

Harmonics and reactive power are just two examples of the increasing complexities of power quality issues.Active filters that employ strategies developed through artificial intelligence are particularly effective at mitigating harmonics and resolving reactive power. Within the scope of this article, we propose the TLBO-trained ANN control technique. as an alternative solution to be used in conjunction with the SAPF. The SAPF's effectiveness is measured and compared in a variety of settings. Matlab-Simulink runs simulations of four different scenarios and presents the findings. According to simulation findings, the proposed ANN-TLBO-based SAPF outperforms alternative scenarios in reducing THD in the source current. The PSO-tuned PI-based SAPF and SAPF with PI controller are also effective. According to the results, this performance improvement is satisfactory (within 5% of the recommended IEEE standard).

A hardware-in-the-loop version of the proposed shunt active filter will be developed for further research. In addition, we plan to improve the SAPF's flexibility by using an ANFIS controller that includes TLBO and other optimization techniques.

Conflict of interest

The authors have no competing interests to disclose.

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