

ANN Based Control Algorithm for Harmonic Elimination and Power Factor Correction Using Shunt Active Filter

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Abstract: The growth in the use of non-linear loads has caused power quality problems like high current harmonics and low power factor. Several control algorithms, which are usually used to resolve harmonic problems and their limitations are discussed in this study. Recently ANN based adaptive shunt active filter gains attention. In this study a new training algorithm for ANN based shunt active filter is proposed. A modification in conventional self-charging technique is also proposed to regulate the dc capacitor voltage at the desired level without the use of PI controller. The design concept of the shunt active filter using the proposed ANN based control algorithm is verified through simulation and the result proved the effectiveness of the proposed algorithm.

Key words: Adaptive shunt active filter, Artificial Neural Networks (ANN), power quality, self-charging

INTRODUCTION

During the past few years, the growth in the use of non-linear loads has caused power quality problems like high current harmonics and low power factor. Non-linear loads appear to be current sources injecting harmonic currents into the supply network through the utility's Point of Common Coupling (PCC). This results in distorted voltage drop across the source impedance, which causes voltage distortion at the PCC. Other customers at the same PCC will receive distorted supply voltage, which may cause over heating of power factor correction capacitors, motors, transformers and cables and mal-operation of some protective devices. Therefore, it is important to install compensating devices (Fig. 1) to eliminate the harmonic currents produced by the nonlinear loads. In fact, many publications have already proposed innovative techniques to alleviate the current harmonics produced by these non-linear loads. The use of ANN for active filtering is very seldom considered.

The application of neural networks as a controller for a shunt active filter for compensation of current harmonics is described in Chen and Connell (1997), Vazquez and Sanmerson (2001), Rukonuzzaman and Nakaoko (2001). Adaline architecture is used in all cases. Adaptive neural network is applied for system harmonic compensation using unified power quality conditioner (Tey *et al.*, 2002). Recently, Tey *et al.* (2005) proposed a control design using ANN to make conventional shunt active filter adaptive (Tey *et al.*, 2005). Also a self-charging technique is proposed in Tey *et al.* (2005) to regulate the dc capacitor voltage at the desired level with

the use of a PI controller. In order to reduce the calculation time, a modified W-H algorithm is explained in Tey *et al.* (2005) which updates only the two weights of the fundamental component. This introduces error in the computation of harmonic reference even through learning rate 'ã' is added. Thus a new training algorithm is proposed which updates the weights of fundamental component as well as harmonic components. It is shown by simulation that the proposed training algorithm converges in less number of iterations compared to algorithm described in Tey *et al.* (2005).

CONVENTIONAL HARMONIC ELIMINATION ALGORITHMS A REVIEW

The current waveform for non-linear load can be represented as

$$i_L(t) = \sum_{n=1}^N I_n \sin(n\omega t + \theta_n) \quad (1)$$

- n • Harmonic order
- N • Order of highest harmonic
- I_n • Magnitude of nth harmonic
- θ_n • Phase angle of nth harmonic

In harmonic extraction procedure the Eq. (1) can be expanded as follows.

$$i_L(t) = \sum_{n=1}^N (I_n \sin n\omega t \cos \theta_n + I_n \cos n\omega t \sin \theta_n) \quad (2)$$

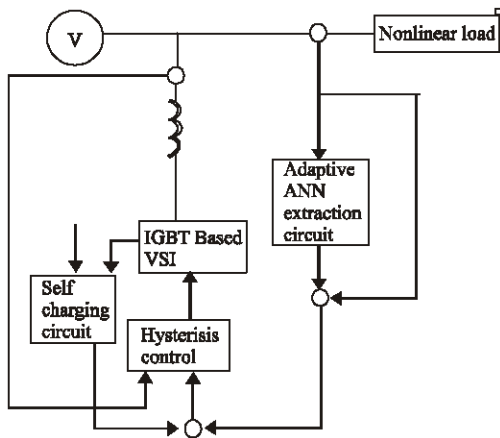


Fig. 1: System block diagram of adaptive shunt active filter

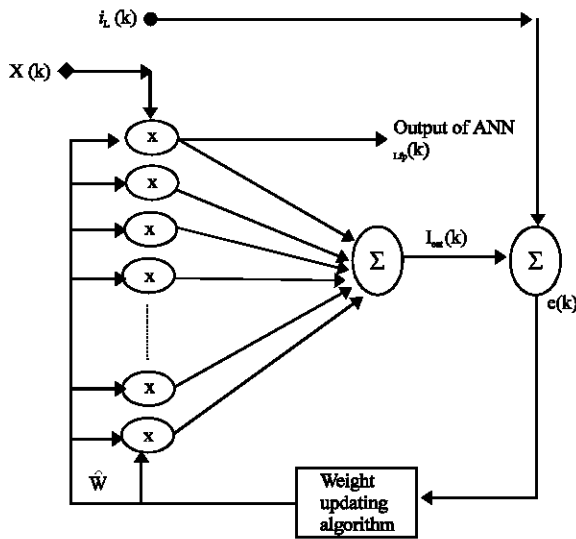


Fig. 2: Conventional adaptive ANN extraction topology

$$i_L(t) = \sum_{n=1}^N (I_{1n} \sin n\omega t \cos \theta_n + I_{2n} \cos n\omega t \sin \theta_n)$$

$$i_L(t) = (I_{11} \cos \theta_1 \sin \omega t + I_1 \sin \theta_1 \cos \omega t + I_2 \cos \theta_2 \sin 2\omega t + I_2 \sin \theta_2 \cos 2\omega t + \dots + I_N \cos \theta_N \sin N\omega t + I_N \sin \theta_N \cos N\omega t)$$

(3)

The term $\sin n\omega t$ and $\cos n\omega t$ corresponds to fundamental frequency and, I_1 and θ_1 gives its magnitude and phase angle, respectively. Similarly $\sin N\omega t$ and $\cos N\omega t$ corresponds to N_{th} harmonic and, I_N and θ_N gives its magnitude and phase angle. Eq. 3 can be written as

$$i_L(t) = W_1 \sin \omega t + W_2 \cos \omega t + W_3 \sin 2\omega t + W_4 \cos 2\omega t + W_{2N-1} \sin N\omega t + W_{2N} \cos N\omega t$$

(4)

where

$$[W]^T = [W_1 W_2 \dots W_{2N}]$$

$$[X]^T = [\sin \omega t \cos \omega t \sin 2\omega t \cos 2\omega t \dots \sin N\omega t \cos N\omega t]$$

The block diagram of adaptive shunt filter and Adeline used for harmonic extraction are shown in Fig. 1 and 2, respectively. The input to the ANN is current waveform sampled at regular intervals. If the current wave form is having 'k' sampling intervals each having sampling time 't_s', then the current at the kth interval is got by substituting $t = k t_s$ in Eq. 4. Thus

$$i_L(k) = W_1 \sin \omega k t_s + W_2 \cos \omega k t_s + W_3 \sin 2\omega k t_s + W_4 \cos 3\omega k t_s + \dots + W_{2N-1} \sin N\omega k t_s + W_{2N} \cos N\omega k t_s$$

(5)

$$[X]^T = [\sin \omega k t_s \cos \omega k t_s \sin 2\omega k t_s \cos 2\omega k t_s \dots \sin N\omega k t_s \cos N\omega k t_s]$$

$$i_L(k) = [W]^T [X]$$

$$i_L(k) = W_1 \sin \omega k t_s + W_2 \cos \omega k t_s + W_3 \sin 2\omega k t_s + W_4 \cos 3\omega k t_s + \dots + W_{2N-1} \sin N\omega k t_s + W_{2N} \cos N\omega k t_s$$

$$= i_{Lfp}(k) + i_{Lfq}(k) + i_{Lh}(k)$$

(6)

where

$$i_{Lfp}(k) = W_1 \sin \omega k t_s$$

$$i_{Lfq}(k) = W_2 \cos \omega k t_s$$

$$i_{Lh}(k) = W_3 \sin 2\omega k t_s + W_4 \cos 3\omega k t_s + \dots + W_{2N-1} \sin N\omega k t_s + W_{2N} \cos N\omega k t_s$$

- i_{Lfp} -Fundamental component of load current inphase with supply voltage a
- i_{Lfq} -Fundamental component of load current in phase quadrature with supply voltage
- i_{Lh} -Harmonic component of load current.

In order to maintain unity power factor, the quadrature component of current has to be supplied by the compensator (shunt active filter). To make the supply voltage free from harmonic distortions, the harmonic component of load current has to be supplied (filtered) by shunt active filter. Thus for harmonic filtering and power factor correction, the reference current for shunt active filter should be $i_{Lr}(k)+i_{Ln}(k)$. It can be estimated by subtracting $i_{Lr}(k)$ from $i_L(k)$.

$$\dot{i}_{Lr}(k) + \dot{i}_{Ln}(k) = \dot{i}_L(k) - \dot{i}_{Lr}(k)$$

The input to ANN is $i_L(k)$ and the output of neuron-1 in Adeline (Fig. 2) gives $i_{Lr}(k)$. The conventional weight updating algorithms are explained below:

Method-1: The windrow-Hoff adaption algorithm often referred to as the windrow-Hoff delta rule, can be used to adapt the adaline's weight vector. The delta rule which minimizes the mean square error between the signal sample $i_L(k)$ and the output $i_{est}(k)$ over all k , can be written as

$$w(k+1) = w(k) + \frac{ae(k) \times (k)}{? + X(k)^T X(k)} \quad (7)$$

- - Reduction factor (learning parameter)
- '•' is a constant chosen to be close to zero and is only included to avoid division by zero.

$$e(k) = \dot{i}_L(k) - \dot{i}_{est}(k)$$

Method-2: This is a modified W-H algorithm where only the two weights of the fundamental component needs to be updated, thus making it independent of the number of harmonic orders present. The modified W-H algorithm is as follows: (Fig. 3)

$$W(k+1) = W(k) + \frac{\gamma e(k) X(k)}{X^T(k) X(k)} \quad (8)$$

Where

$$W = \{W_1, W_2, X(k) = \begin{matrix} \sin \omega k t_s \\ \cos \omega k t_s \end{matrix}$$

and '•' is the learning rate.

The speed of the iteration is greatly enhanced. However, by updating only the two weight elements, it will result in a large $e(k)$.

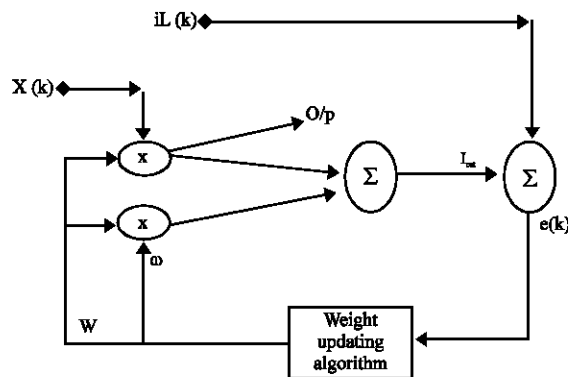


Fig. 3: Simplified ANN used in Tey *et al.* (2005)

PROPOSED ALGORITHM

Mathematical formulation: If 'F' denotes iteration count then

$$[i_L(F)] = \begin{matrix} i_L(t_s) \\ i_L(2t_s) \\ \vdots \\ i_L(Kt_s) \end{matrix} \quad (9)$$

The sampled output vector is

$$[i_R] = \begin{matrix} i_{R1} \\ i_{R2} \\ \vdots \\ i_{Rk} \end{matrix} \quad (10)$$

Equation 16 can be calculated using Eq. 5 by substituting $k = 1, 2, \dots, \dots, k$.

The error vector is

$$[E(F)] = [i_R] - [i_L(F)] \quad (11)$$

$$[W(F)] = \begin{matrix} W_1 \\ W_2 \\ \vdots \\ W_{2N-1} \\ W_{2N} \\ \omega \end{matrix} \quad (12)$$

$$\frac{\delta i_L(k)}{\delta \omega} = \frac{kt_s(W_1 \cos \omega kt_s - W_2 \sin \omega kt_s + 2W_3 \cos 2\omega kt_s - 2W_4 \sin 2\omega kt_s + \dots + NW_{2N-1} \cos N\omega kt_s - NW_{2N} \sin \omega kt_s)}{\delta \omega} \quad (13)$$

The sub matrix) $\frac{\delta i_L(F)}{\delta W}$ is given by

$$\begin{matrix} \sin \omega kt_s \cos \omega kt_s, \dots, \sin N\omega kt_s \cos N\omega kt_s \\ \sin 2\omega kt_s \cos 2\omega kt_s, \dots, \sin 2N\omega kt_s \cos 2N\omega kt_s \\ \sin 3\omega kt_s \cos 3\omega kt_s, \dots, \sin 3N\omega kt_s \cos 3N\omega kt_s \\ \vdots \\ \vdots \\ \sin k\omega t_s \cos k\omega t_s, \dots, \sin 3Nk\omega t_s \cos 3Nk\omega t_s \end{matrix} \quad (14)$$

The sub matrix $\frac{\partial i_L(F)}{\delta \omega}$ is given by

$$[N] = \frac{\delta i_L(F)}{\delta \omega} = \begin{matrix} \frac{\delta i_L(t_s)}{\delta \omega} \\ \frac{\delta i_L(2t_s)}{\delta \omega} \\ \vdots \\ \frac{\delta i_L(Kt_s)}{\delta \omega} \end{matrix} \quad (15)$$

The elements of [N] sub matrix can be calculated using Eq. 13 by substituting $k = 1, 2, \dots, k$

$$[J] = MN \quad (16)$$

M and N are the sub matrix of [J]

$$[L] = \begin{matrix} \Delta W_1 \\ \Delta W_2 \\ \vdots \\ \Delta W_{2N-1} \\ \Delta W_{2N} \\ \Delta \omega \end{matrix} \quad (17)$$

The [L] Matrix can be calculated using the equation given below:

$$\begin{matrix} [E(F)] = [J][L] \\ [L] = [J]^{-1} [E(F)] \end{matrix} \quad (18)$$

New fast tracking algorithm

Step-1: Set the error tolerance value ϵ and iteration count $F = 0$.

Step-2: Initialize [W (F)] matrix given in Eq. 12

Step-3: Calculate $[i_L (F)]$ matrix given in Eq. 9 using Eq. 5

Step-4: Calculate [E (F)] matrix using Eq. 11

Step-5: Check whether the largest element of [E (F)] is less than ϵ . If Yes, go to Step 10. Else go to next step.

Step-6: Calculate the Sub Matrices [M] and [N] of [J] using Eq. 14 and 15 and form [J] matrix as per Eq. 16

Step-7: Calculate [L] Matrix using Eq. 17

Step-8: Update [W (F)] matrix using equation

$$[W(F)] = [W(F)] + [L]$$

Step-9: Set iteration count $F = F + 1$ and go to step-3

Step-10: Using the element of $[W (F)]$ calculate current reference.

PERFORMANCE ANALYSIS

In order to check the validity and performance of the proposed algorithm compared to the conventional methods, numerical experimentation on the simulated waveform has been carried out using MATLAB software package. The neural estimation algorithm is initialized, by finding an optimized weight vector starting from a random set and minimizing an integral error square criterion. A sample rate of 81 based on the 50 Hz frequency is chosen for the estimation of signal amplitude and phase for all the studies. As a test case, the following sinusoidal signal corrupted by harmonic is chosen.

$$\begin{aligned} i_L(t) = & [1.5\sin(\omega t + 29.3^\circ) + 0.068\sin \\ & (\omega t + 141.6^\circ) + 0.017\sin(7\omega t + 66.2^\circ) \\ & + 0.022\sin(11\omega t - 99.4^\circ) + 0.024\sin \\ & (13\omega t - 179.2^\circ) + 0.012\sin(17\omega t - 1.3^\circ)] \end{aligned}$$

The above wave form pertains to an industrial load described in reference Sira and Zak (1984). The results of simulation are tabulated below for comparison. It is concluded that the proposed neural algorithm produces a faster convergence with lesser steady state error (Table 1).

Table 1: The wave form pertains to an industrial load

Sl. No	Training algorithm	No.of epochs	Accuracy(%)
1	Method-1	738	90.15
2	Method-2	355	93.18
3	Method-3	540	93.18
4	Method-4	336	90.91
5	Proposed algorithm	239	93.18

MODIFIED SELF CHARGING CIRCUIT

To regulate the dc capacitor voltage at the desired level, an additional real power has to be drawn by the adaptive shunt active filter from the supply side to charge the two capacitors. The energy 'E' stored in each capacitor can be reprinted as Where 'C' is the value of each capacitor and Vdc/2 is the voltage of each capacitor can be reprinted as

$$E = \frac{1}{2} C \frac{V_{dc}}{2}^2$$

Where 'C' is the value of each capacitor and Vdc/2 is the voltage of each capacitor.

If the desired level of voltage across each capacitor is $V_{dc(ref)}/2$, the energy for capacitor is

$$E^1 = \frac{1}{2} C \frac{V_{dc(ref)}}{2}^2$$

The difference between E^1 and E represents the additional energy required by capacitor to reach the desired voltage level. Thus

$$\Delta E = E^1 - E = \frac{1}{2} C \left[\frac{V_{dc(ref)}}{2}^2 - \frac{V_{dc}}{2}^2 \right]$$

On the other hand the charging energy E_{ac} delivered by the three-phase supply side to the inventor of each capacitor will be

$$E_{ac} = 3pt \\ = 3(E_{rms} I_{dc(rms)} \cos \Phi)t$$

P = Additional real power required

V_{rms} - rms value of the instantaneous supply voltage

$I_{dc(rms)}$ - rms value of the instantaneous charging current.

• - Phase deferece between the supply voltage and charging current

t - Charging time.

However, 't' can be defined as T/2 since the charging process only takes place for half a cycle for each capacitor, where 'T' is the period of supply frequency. By using Phase Lock Loop (PLL) the charging current is made in phase with the supply voltage. Thus $\cos \bullet = 1$. Also the rms value can be expressed in terms of maximum values.

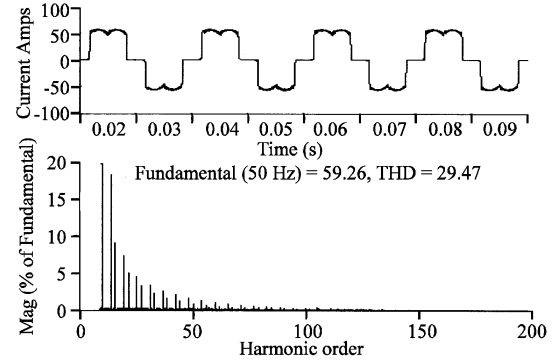


Fig. 4: Source current before filtering with its harmonic spectrum

This results in

$$E_{ac} = 3 \frac{V}{\sqrt{2}} \frac{I_{dc}}{\sqrt{2}} \frac{T}{2}$$

Neglecting the switching losses in the inverter and according to the energy conservation law the following Equation holds.

$$\Delta E = E_{ac}$$

$$I_{dc} = 2C \frac{\left\{ [V_{dc(ref)}]^2 - [V_{dc}]^2 \right\}}{3VT} \quad (19)$$

The configuration of three-phase self-charging current is shown in Fig. 4. The PLL synchronizes itself with the supply voltage of phase 'a' and outputs three sine waves, which are 120° out of phase from each other. These sine waves are multiplied with I_{dc} to obtain the three-phase i_{dc} . Thus the three phase injection currents can be calculated as

$$\begin{aligned} i_{inj,a} &= i_{Lf,qa} + i_{Lh,a} - I_{dc} \sin \omega t \\ i_{inj,b} &= i_{Lf,qb} + i_{Lh,b} - I_{dc} \sin(\omega t - 120) \\ i_{inj,c} &= i_{Lf,qc} + i_{Lh,c} - I_{dc} \sin(\omega t + 120) \end{aligned} \quad (20)$$

The minus sign of the third term indicates that the charging current i_{dc} flows into the VSI. A hysteresis controller is used to control the switching of the VSI.

SIMULATION STUDIES

The adaptive ANN extraction circuit, self-charging circuit, hysteresis control and injection circuit are integrated as an over all mode of adaptive shunt filter.

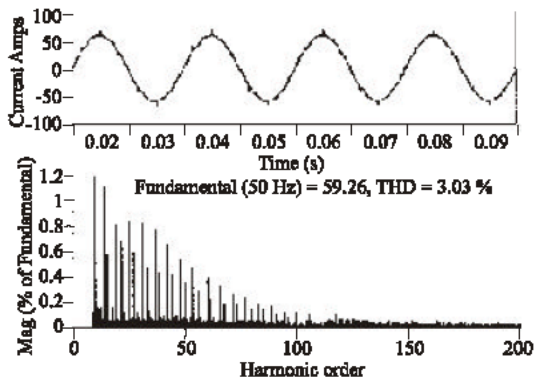


Fig. 5: Source current after filtering with its harmonic spectrum

A three-phase distribution system is built using MATLAB and the ANN Based shunt active filter using proposed algorithm and modified self-charging circuit is simulated.

Supply Voltage = 230 (rms)
Filter inductance = 1.1 mH
Filter Capacitance = 2200 μ F
Reference D.C voltage = 650V

The above waveforms show the effectiveness of the proposed algorithm (Fig 5).

CONCLUSION

In this study, a new control design for the shunt active has been presented. The control design is based an artificial neural networks that use a new fast tracking training algorithm. With the use of this artificial neural network algorithm, the functionalities of the shunt active filter are enhanced. Self-charging capability is also integrated in the proposed shunt active filter, which does not uses PI controller unlike traditional approaches.

Simulation results have verified the design concept of the proposed ANN based shunt active filter to be highly effective and robust. However, the proposed concept still needs to be validated experimentally.

ACKNOWLEDGEMENT

The authors are grateful to Robin Research Trust for having magnanimously permitted them to avail the facilities in their Simulation lab for the successful completion of this research work.

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