Adaptive Radial Basis Function Neural Networks-Based Real Time Harmonics Estimation and PWM Control for Active Power Filters

Eyad KH Almaita

Western Michigan University, eyad.k.almaita@gmail.com

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ADAPTIVE RADIAL BASIS FUNCTION NEURAL NETWORKS-BASED REAL TIME HARMONICS ESTIMATION AND PWM CONTROL FOR ACTIVE POWER FILTERS

by

Eyad KH Almaita

A Dissertation
Submitted to the
Faculty of the Graduate College
in partial fulfillment of the
requirements for the
Degree of Doctor of Philosophy
Department of Electrical and Computer Engineering
Advisor: Johnson A. Asumadu, Ph.D.

Western Michigan University
Kalamazoo, Michigan
April 2012
THE GRADUATE COLLEGE
WESTERN MICHIGAN UNIVERSITY
KALAMAZOO, MICHIGAN

Date 2/17/2012

WE HEREBY APPROVE THE DISSERTATION SUBMITTED BY

EYAD KH ALMAITA

ENTITLED ADAPTIVE RADIAL BASIS FUNCTION NEURAL NETWORKS-BASED
REAL TIME HARMONICS ESTIMATION AND PWM CONTROL FOR
ACTIVE POWER FILTERS

AS PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE

DEGREE OF Doctor of Philosophy

Electrical and Computer Engineering
(Department)

Electrical and Computer Engineering
(Program)

Dr. Johnson Asiamadu
Dissertation Review Committee Chair

Dr. Ala Al-Fuqaha
Dissertation Review Committee Member

Dr. Liang Dong
Dissertation Review Committee Member

APPROVED

Dean of The Graduate College

Date April 2012
With the proliferation of nonlinear loads in the power system, harmonic pollution becomes a serious problem that affects the power quality in both transmission and distribution systems. Active power filters (APF) have been proven to be one of the most successful methods for mitigating harmonics problems. So far, different techniques have been used in harmonics extraction and control of APF to satisfy the fast response and the accuracy required by the APF. Neural networks techniques have been used successfully in different real-time and complex situations. This dissertation demonstrates four main tasks; (i) a novel adaptive radial basis function neural networks (RBFNN) algorithm. This algorithm can be used in different signal processing or control applications,(ii) dynamic identification for the total harmonics content in converter waveforms based on RBFNN and p-q (real power-imaginary power) theory, (iii) RBFNN is used to dynamically identify and estimate
selective harmonic components in converter waveforms, and (iv) a novel adaptive hysteresis current control algorithm with nearly constant switching frequency.

The proposed RBFNN filtering algorithms are based on a computationally efficient training method called hybrid learning method, which requires negligible training time. Both of the proposed algorithms in this dissertation, adaptive RBFNN algorithm and adaptive hysteresis current controller, are simple, effective, and easy to implement.
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Eyard KH Almaita
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CHAPTER 1

BACKGROUND AND MOTIVATION

1.1 Introduction

Recently, the power quality term has received more attention from both electric utility and electrical power customers. Several factors have brought power quality problems to the attention of utilities and customers; the more sensitive load equipment to power variation, the increasing harmonics level in power system, the increasing awareness of customers about power quality issues, and the network interconnection that magnify the impact of the failure of any network components. A suitable definition of power quality problem could be any deviation of voltage, current, and/or frequency that cause failure or misoperation of electrical equipments [1]. Harmonic pollution has become a serious problem that affects the quality of power in both transmission and distribution of power systems because the proliferation of nonlinear loads. The problems caused by harmonics include malfunctioning of fuses or circuit breaker relays, heating of conductors and motors, insulation degradation, and communication interference [2-4]. Because of these problems, harmonics mitigation in power system has become one of the most challenging problems in power system.

The most common power filters compensate for harmonic voltages and currents are passive filters. Even though passive filters are cheap and easy to operate,
they have low harmonic bandwidth (need several filters to compensate for a wide spectrum harmonics), can be subjected to resonance (series or parallel resonance with power system reactance), have large size (big capacitor banks or bulky inductors), and are affected by source impedance [5, 6].

Active Power Filters (APF), which are more dynamics, have been introduced as an effective means to overcome the problems associated with passive filters. The objective of an APF is to ensure that the power source feeds only active and harmonic-free power to the load. A nonlinear load draws reactive power and harmonic components. The basic principle of APF is to measure the system parameters (current or/and voltage), calculate the reference signal, realize this reference signal by power converter, and inject a signal that meets the compensation objectives.

The most crucial parts for the success of the compensating process by APF are the harmonic extraction technique and control technique used in APF. Different strategies have been applied for both parts (harmonic extraction and control) since APFs were introduced. One of the most potential techniques for both harmonic extraction and control is the use of artificial neural networks. The three main techniques used in artificial neural networks techniques are (i) the adaptive linear neuron (ADALINE), (ii) the popular back propagation neural networks (BPNN), and (iii) the radial basis neural networks (RBFNN). The RBFNNs have several advantages over ADALINEs and BPNNs; capable of approximating highly nonlinear
functions, its structured nature facilitates the training process because the training can be done in a sequential manner, and the use of local approximation can give better generalization capabilities[7, 8]. Even though RBFNNs have been used for harmonic detection, the number of hidden neurons is still large and still uses an algorithm similar to that of BPNN. This makes RBFNN networks subjected to the same problems found in BPN [9]. There are several studies that dealt with harmonics extraction using neural networks but still there is a gap in these studies in terms of: the capability of these networks to work over a wide operating range of harmonics, the size of the resulted neural network, the long training time, and the ability of these networks to adapt after the end of training phase.

In the control part, among the many algorithms used to control APF, hysteresis current control (HCC) is considered the most suitable algorithm because it is fast, easy to implement, accurate, and unconditionally stable [10, 11]. The conventional HCC algorithm has a few drawbacks such as variable switching frequency and interference between phases in three phase case [12-16]. Several papers tried to tackle the variable switching frequency for the HCC, many of these papers end up with control algorithms that complicate the HCC algorithms and make it lose its simplicity. Still, there is a need to an effective, and easy to implement control algorithm for the HCC without losing the good merits of the conventional HCC.
1.2 Research Goals

In this research there are two main goals. The first goal of this research is to investigate the construction of radial basis function neural networks for on-line harmonic extraction under the following conditions:

- Relatively small error.
- The ability to do the on-line harmonic extraction over a wide operating range, for a given non-linear load.
- Relatively short training time.
- Small size of the neural network.
- The ability to adapt after finishing the training phase.

The second goal is to investigate the construction of a hysteresis current controller with the following characteristics:

- Simple.
- Accurate.
- Easy to implement.
- Have nearly constant switching frequency.
CHAPTER 2

PERTINENT LITERATURE

2.1 On Harmonic Extraction

Different harmonic extraction techniques were used in the literature. These techniques can be divided into three main techniques: frequency domain techniques, time domain techniques, and artificial intelligent neural networks techniques.

2.1.1 Frequency Domain Techniques

Harmonic detection methods in frequency domain depend mainly on the Fourier transform. These detection methods transform the distorted current or/and voltage signals from the time domain to the frequency domain, isolate the fundamental component from the harmonics in the frequency domain, and then reconstruct the compensating signal.

Girgis et al. [17] and Mariethoz [17, 18] put some conditions to the use of the discrete Fourier transform (DFT) or the fast Fourier transform (FFT) for harmonic detection: the signal to be processed must be periodic, the samples window length must represent an integer number of fundamental cycles, the sampling frequency equals or greater than twice the highest harmonic order in the signal, and each of the harmonics included in the signal is an integer multiple of the fundamental frequency.

Komrska et al. [19] tried to avoid the high computation requirement for the classical DFT. In their work, they estimated the fundamental harmonic instead of the whole
spectrum of the signal, in order to reduce the computational complexity. Although this technique saves computations relative to the classical DFT, still demands need computational complexity, which makes this technique unsuitable for on-line application.

Han [20] used the FFT algorithm to extract the harmonic components in the load current. The FFT algorithm is computationally more efficient than DFT, because for a sample with length N, FFT performs two DFT with N/2 points instead of N DFT points (which reduces the calculations from $N^2$ to $N \log_2(N)$ ). The main problem of using FFT for online harmonic extraction is that can’t be performed in each sampling period. Instead, an averaging for magnitude and phase is made to overcome the error due to the sampling. Also compensation for phase delay is needed.

Borisov [21] and Maza-Ortega [21, 22] used a version of DFT suitable for on-line application Called Recursive Discrete Fourier Transform (RDFT) which is more efficient than the DFT or FFT methods. The RDFT technique is different from the classical DFT by using a sliding window; this window is shifted usually one sample. The spectrum of the window at time $k$ is different from the spectrum of the window at time $k-1$ by the first and the last sample. Therefore there is no need to calculate the spectrum for the whole window. The results show a feasibility of applying this technique in real-time applications.

Different reviews and comparative studies [23-25] addressed the main drawbacks of using frequency detection methods such as the leakage problem, the synchronization
between the sampling frequency and the fundamental frequency, the large memory
needed, large number of computations, and the poor transient performance.

2.1.2 Time Domain Techniques

2.1.2.1 Filter Based Methods

The filter based methods depend on extracting the harmonics directly from the
current/voltage signal by passing the signal through the time domain filter.
El-Habrouk et al. [23, 24] and Green [24] discussed the using of high-pass filter to
remove the low order harmonics. The filtered signal becomes the reference signal.
This technique is called the direct extraction technique. Figure 2.1 illustrates the basic
principle of this technique. One of the major drawbacks of direct extraction technique
is the sensitivity to the noise that appears during the transient phase. Also there is a
delay in the reference signal due to the nature of causal filters.

![Figure 2.1 Direct Harmonic Extraction Technique](image)

Moran et al. [26] used low-pass filter to extract the fundamental harmonic of the load
current. The fundamental harmonic (the filter output) is subtracted from the original
signal. The result is the harmonic contents in that signal which becomes the reference
signal. Figure 2.2 illustrates the basic idea of this technique, which is called indirect
extraction technique. This technique is preferable than the direct technique because it is more stable during transients and any delay, because of the causal filter nature, appears in the fundamental harmonic not in the higher order harmonics.

\[ x(t) \rightarrow \text{Low-Pass Filter} \rightarrow x_h(t) \]

**Figure 2.2 Indirect Harmonic Extraction Technique**

Quinn *et al.* [27] and Wong *et al.* [27, 28] used notch filters to isolate the fundamental harmonic from the load current, which is similar to the high-pass filter method but in a more precise way.

In general, in time domain filters there is a tradeoff between the attenuation and the phase delay (the higher attenuation the higher phase delay and vice versa), and faster transition time can cause oscillations.

### 2.1.2.2 Instantaneous Power Theory

Akagi *et al.* [29] introduced the most popular technique for harmonic extraction, which is called the instantaneous power theory. Akagi *et al.* [30] discussed in more details the use of Instantaneous power theory or (p-q) theory to compensate the harmonics and reactive power in power systems. Figure 2.3 illustrates the basic principle of the p-q theory. It consists of transforming the voltages and currents from a-b-c domain to a stationary frame called α-β-0 domain. Then the α-β-0
domain voltages and currents are used to calculate the active power ($p$) and imaginary power ($q$). The $p$ or/and $q$ are decomposed into their respective fundamental parts (also called constant parts) and harmonic components (also called oscillating parts). The decomposed $p$ or/and $q$ are used to calculate the reference currents in the $\alpha$-$\beta$-$0$ domain as shown in [29, 30]. The reference currents are transformed from $\alpha$-$\beta$-$0$ domain to $a$-$b$-$c$ domain. Then a power converter circuit is used to inject currents (equal to the reference currents) to cancel the harmonics or/and the reactive power contained in the source currents.

Figure 2.3 Block Diagram of the p-q Theory

The success of the $p$-$q$ algorithm depends on the methodology used for the decomposition of the $p$ or/and $q$ signals into their constant and oscillating parts. Several techniques have been used $p$ and $q$ decomposition.
Akagi et al. [30] used high-pass filter and low-pass filter to decompose the power components. But the results show that the low-pass filter is preferable over the high-pass filter method due to the delay during transient intervals in the high-pass filter. But both methods still have the same disadvantages regarding the compromising between the attenuation and the phase delay.

Nakata [31] used two moving average filters to separate the active power components and imaginary power components. This technique shows good results in $p$-$q$ theory, but .

2.1.2.3 Synchronous Reference Frame Method

Gondat et al. [32] and Santiprapan [32, 33] discussed the use of Synchronous Reference Frame (SRF) Method. Figure 2.4 illustrates the SRF algorithm. This algorithm includes transformation of the three-phase load currents from $a$-$b$-$c$ domain to a stationary frame called $\alpha$-$\beta$-$0$ domain by using Clarke Transformation. The currents are transformed from $\alpha$-$\beta$ domain to a synchronous moving frame called $d$-$q$ domain using Park transformation. The $d$-current component $i_d$ (also called the direct current component). Similarly the $q$-current component $i_q$ (also called the quadrature current component) can also been broken up into the fundamental component and oscillating components. The decomposed direct and quadrature currents components are the reference currents. The reference currents are then transformed form $d$-$q$ domain to $\alpha$-$\beta$-$0$ domain using inverse park Transformation. Then $\alpha$-$\beta$-$0$ domain reference currents are finally transformed to the
reference $a-b-c$ domain currents using inverse Clarke Transformation. Then a power converter circuit is used to inject currents (equal to the reference currents) to cancel the harmonics or/and the reactive power contained in the source currents.

Similar techniques to that used in $p-q$ method are used to separate the constant parts of $i_d$ and $i_q$ from the oscillating parts. One of the main problem in this algorithm is the need to estimate the fundamental frequency using PLL, which will add more computational cost and complicate the extraction process.

```
Figure 2.4 Synchronous Frame Method Block Diagram
```

### 2.1.2.4 Neural Networks Methods

The Artificial intelligent filters have been introduced to overcome the disadvantages of the time and frequency domain filters. The three main techniques
used in artificial intelligent filtering are (i) adaptive linear neuron (ADALINE), (ii) Feed Forward Multilayer Perceptron (MLP), and (iii) radial basis function neural networks (RBFNN).

I. Adaptive Linear Neuron (ADALINE)

The ADALINE algorithms are the most popular neural networks techniques used in active power filters. The simplicity and the ease of hardware implementation are the main reasons behind the popularity of this algorithm. The ADALINE network has the following features: (i) it consists of one neuron, (ii) it is used as online identifier, (iii) the relationship between the input and the output is linear, and (iv) it uses least mean square error methods (LMS) to adjust its weights.

Zouidi et al. in [34] and Bhattacharya et al. in [34, 35] used the ADALINE to identify the discrete Fourier expansion coefficients of harmonic polluted waveform. The magnitude and the phase of the fundamental harmonic can be estimated based on these coefficients. Figure 2.5 illustrates the block diagram of the ADALINE algorithm. The inputs of this network represent the harmonics presents in the polluted load current (the more inputs the more accurate the model). The weights of this network represent the Fourier expansion coefficients. The output of this network is the weighted sum of the inputs multiply by a constant (represented by the PureLine box). The error between the estimated load current and the actual load current is used to update the weights, based on Widro-Hoff algorithm [34].
The ADALINE performance depends on the number of harmonics included in its structure. The convergence of the ADALINE slows as the number of harmonics included increases and also subjected to fall in local minima [24].

Gupta et al. [36] and singh [36, 37] used ADALINE scheme to estimate the fundamental frequency component of load current based on pattern recognition. An ADALINE network was trained offline to extract the fundamental component of a harmonic-polluted signal. The input of this network is a delayed vector of N data points. The weights are also updated based on Widro-Hoff algorithm. The problem of the ADALINE scheme, that it cannot map nonlinear functions.

II. Feed Forward Multilayer Perceptron (MLP)

Chen et al. [38] used multi-Input multi-output MLP neural network with back propagation algorithm to estimate the total harmonic contents for a three-phase
nonlinear load. Figure 2.6 shows the neural network structure used by Chen. In Chen’s proposed scheme, the firing angle (for the nonlinear load) in generating training data was constant. Several remarks can be noted on Chen’s proposed scheme: the architecture need to be tested for a wide range, the number of hidden neurons is large, also the training time is not mentioned.

![MLP Neural Networks Architecture by Chen](image)

Figure 2.6 MLP Neural Networks Architecture by Chen

Nascimento et al. [39] used a twelve multilayer neural networks to estimate the Fourier expansion coefficients for the first six harmonics. Each pair of these neural networks are used to estimate the Fourier coefficients $A_n$ and $B_n$ for a given harmonic order. There is little information about the training time and the training data.

Zouidi et al. [40] used MLP neural networks to estimate the total harmonics content in current signal. Figure 2.7 shows the neural network architecture used by Zouidi. The load current value and the value of $-\sin(wkT)$, which represents the fundamental current, are used as the inputs of the neural networks and the network output is the
total harmonics content. In this dissertation the operating range doesn’t seem wide. Also, an estimation of the value of fundamental angular frequency (w) is required.

Mazumdar et al. [41] combined the SRF theory and MLP neural networks to extract the harmonics in three-phase nonlinear load current. The objective of the neural network is to predict, in one-step ahead, the values of the three-phase currents. Figure 2.8 shows the neural network structure used by Mazumdar. The values of the three-phase voltages and currents and their delays (two delays) are used to predict the values of the currents during on-line training process. These predicted values are used as the inputs for the SRF algorithm (illustrated above) to extract the harmonics content in the load currents. In Mazumdar proposed scheme: the training time is long, the operating range is limited, and the number of hidden neurons is large.
III. Radial Basis Function Neural Networks (RBFNN)

Chang et al. [9] used radial basis function neural networks to extract selective harmonics. Figure 2.9 shows the neural network structure used by Chang. A delayed vector of the polluted signal is used as the input and the output of the network is the value of the given harmonic order (first, third, fifth, or seventh). The error between the RBFNN output and the desired output (just in the training phase) is used to update the values of weights and centers based on training algorithm similar to the back propagation algorithm used in MLP. This proposal utilizes some of the capabilities of RBFNN but it uses similar training algorithm of the back propagation, which make this network subjected to fall in local minima. Also the operating range for the nonlinear load signal is small.
Masjedi *et al.* [42, 43] used off-line adaptive learning algorithm for the RBFNN to extract the harmonic. This algorithm is based on adding or removing one-hidden neuron at a time based on the error between the RBFNN output and the desired output. Neither the number of hidden neuron nor the training time is mentioned.

### 2.2 On Current Control Techniques

The performance of active power filter is highly affected by the choice of the control technique. Several current control techniques have been used for active power filters [14, 44-52] such as space vector control, Proportional-Integral (PI) control, predictive control, deadbeat control, resonant control, sliding mode control, carrier phase shift SPWM, hysteresis current control, fuzzy control, and artificial neural networks control. Among these control techniques hysteresis current control technique shows performance superiority over the other control technique used in
active power filter applications [53-56]. The main advantages of the hysteresis current controller are [53-55]:

- Simple and easy to implement.
- Fast response.
- Accurate.
- Unconditionally stable.

The basic architecture of the hysteresis current control exhibits some drawbacks such as variable switching frequency and phase interference in three-phase case [15]. Several improvements on the basic hysteresis current control technique were made to tackle the drawbacks of the basic technique. The main techniques used to improve the basic hysteresis technique are:

- Space-vector based hysteresis current controllers.
- Adaptive hysteresis band current control technique.
- Fuzzy based hysteresis current controller.
- Neural network based hysteresis current controller.

### 2.2.1 Space –Vector Based Hysteresis Current Controller

This technique combined the conventional space vector pulse width modulation (PWM) with hysteresis current control. In this technique the three phase current errors are manipulated as space vector. This manipulation gives this technique the ability to compensate the phase-voltages interactions, which lead to the reduction
of the switching frequency [46]. Different algorithms on space-vector based hysteresis current controller have been introduced.

Ling et al. [57], Zhang et al. in [58], and Xu Dianguo et al. in [59] used current error space-vector based hysteresis controller algorithm to keep the current error in hexagonal boundary. The derivatives of the three current errors (reference current-actual current) are used to determine the desired space voltage vectors. These space voltage vectors are used to drive the active power filter (inverter) to one of eight unique switching states. The variation in the switching frequency is considered the major problem in this technique [60]. Different boundary shapes were used in the literature; square boundary [61], parabolic boundary [62], and circular boundary [63, 63].

Zeng et al. [64] used two loops of comparators (outer loop and inner loop) to build three level comparators (+1, 0, -1). These comparators are used to find the optimal voltage space vector that will return the current error to the inner loop. This method still suffers from the variation of the switching frequency.

Suul et al. [55] used the space-vector based hysteresis control in synchronous reference frame. In this approach, the current error is calculated in d-q reference frame. This is done by measuring the three-phase currents in a-b-c domain and transforming these currents to d-q domain, which needs phase locked loop (PLL) to obtain the frequency. The current errors in d-q domain are the inputs for three-level comparators. The outputs of the comparators are used as the input of a switching
table. This switching table ensures that the select voltage vector is the closest to the previous switching state, which ensures the reduction of the switching frequency. One of the drawbacks for this approach is the need for PLL, which may lose synchronization in transient intervals.

2.2.2 Adaptive Hysteresis Band Current Control Technique

The adaptive hysteresis band current control technique was introduced by Bose [13] to maintain the switching frequency nearly constant. In Bose’s proposal, the hysteresis band is changed as a function of load and supply parameters. Bose’s proposal was introduced as an application of motor drive. Different techniques based on the original adaptive hysteresis band current control were applied on the active power filter applications. Dalvand [65], Jog [66], Wenjin [67], and Charles [68] adapted the Bose’s algorithm as modulation technique for different topology of active power filters. Figure 2.10 illustrates the basic principle of the adopted algorithm. The hysteresis band of each phase is calculated continuously as a function of the phase reference current, the supply voltage, and the voltage of DC link. This method is considered a popular method in the adaptive hysteresis band in active power filter application. The major drawback of this method is the need to estimate the system parameters and the continuous calculation of the derivative of each phase current.
Tsengenes [69] used a simple method to calculate the width of the hysteresis band. Figure 2.11 illustrates the principle of this method. In this method, the load current is passed through a low-pass filter and the RMS value of the output of the low-pass filter is calculated. Then the hysteresis band is considered to be proportional to the load current and calculated as a percentage (shown as $k$ in figure 2.11) of the RMS value of the low-pass filter. In Tsengenes’ proposal, the ability to maintain constant switching frequency and the inference of $k$ is not mentioned.
Ouyang et al. [70] used similar technique as in [69] but their technique depends on the absolute summation of the three-phase reference currents. The technique can be summarized as: calculate the sum of the absolute value of the three-phase reference current, continuously pass the value of this sum through low-pass filter to calculate the average value, compare the output of the low-pass filter with the actual current to determine the current fluctuation range, then the hysteresis band is obtained as a proportional percentage to the current fluctuation range. Also in Ouyang’s proposal, the ability to maintain constant switching frequency is not mentioned.

Malesani et al. [16] used different technique based on the estimation of the hysteresis band as the summation of two separate estimation systems. The first system is to estimate the first value of hysteresis band based on the variation of the output voltage. The second system is to estimate the second value of hysteresis band based on phase displacement using PLL. The hysteresis band is calculated as the sum of the first and the second hysteresis bands. The need for the PLL and the complication of the hysteresis band calculation method make the hysteresis band lose the simplicity.

### 2.2.3 Fuzzy Based Hysteresis Current Controller

Li Jun [71] used fuzzy controller to realize adaptive hysteresis band current controller. The reference current and the current error are used to adjust the hysteresis band based on linguistic fuzzy rules. The ability to have constant frequency by this
technique is not shown in [68]. Also the number of fuzzy rules is small, which affect the smoothness of the controller.

Dongmei et al. [72] proposed an adaptive hysteresis band using fuzzy controller. This controller used the current error and the rate of the error to estimate the hysteresis band based on fuzzy rules. The main objective in Dongmei’s proposal, is the reduction of the tracking error compare to the conventional hysteresis controller. Also the constant frequency switching is not discussed by Dongmei’s proposal.

Pereira et al. [73] tried to reduced the complexity in estimating the load parameters [13, 74] and the current derivatives [13, 74]. In their dissertation, a digital hysteresis current controller is built based on fuzzy controller that depends on the sign of the current error to give the switching signal. Although, the switching frequency in this technique is constant, the current ripple seems to depend on the load parameter.

In general to have an effective fuzzy based hysteresis current controller, the number of fuzzy rules must be large enough [75] to have a smooth control action.

2.2.4 Neural Networks Based Hysteresis Current Controller

The modern control of power electronics tends to utilize the power of artificial intelligence, especially the neural networks [76, 77]. Recently, different neural networks algorithms have been applied to the control of active power filters. These algorithms include the use of direct inverse control, PI-neural control, space vector control, and hysteresis control [78-81]. This section will discuss neural networks
algorithm used to improve the performance of hysteresis current controller in active power filter applications.

The authors in [82-86] used feedforward neural networks with backpropagation algorithm to replace the conventional hysteresis current controller with neural networks based hysteresis controller. In these controllers, the current error and a delayed sample of the same current error are used to generate the switching signals. All the disadvantage of the conventional hysteresis controller are inherited in this controller

Wang et al. [75] used backpropagation neural networks to implement a hysteresis current controller with adaptive hysteresis band. The current error and a delayed sample of the same current error are used to adjust the hysteresis band. The training data acquisition and the switching frequency are not explained by Wang.
3.1 Active Power Filter

An active power filter (APF) is a power converter circuit used to mitigate the power quality problems such as reactive power compensation, harmonics mitigation, and harmonic damping. Since it was introduced, APFs received strong attention from researchers in electrical power fields. This attention led to the different classification of APFs based on converter configuration, topology of APF, application, and control strategies [23, 87-90]. The main goal of APF is to improve the power quality. This can be achieved by sensing the system parameters, calculating the reference signal, and realizing this reference signal by power electronics converter.

3.1.1 Classification of APFs Based on Their Topology

3.1.1.1 Shunt Active Power Filter

Shunt APF is considered the most popular topology of APFs. The main purpose of the shunt APF is to compensate harmonics of the load current, it cannot be used for compensating the harmonics of the voltage-source harmonic loads [91]. Figure 3.1 shows the system configuration of the shunt APF. The shunt APF is driven by a controller to draw a compensating current $I_c$ from the source. This compensating...
current is equal to the sum of the harmonics and the reactive currents drawn by the non-linear load. Theoretically, the resultant source current ($I_s$) should be harmonic free and in-phase with the AC mains voltage [88, 89, 91].

![Diagram of Shunt APF by Singh](image)

**Figure 3.1 Shunt APF by Singh**

**3.1.1.2 Series Active Power Filter**

Series APFs are more suitable for harmonic-voltage source loads. Figure 3.2 shows the system configuration of the series APF. The series APF is connected to utility in series via matching transformer. The series APF generate voltage \( V_{APF} \) such that [88, 91]:

\[
V_{APF} = K \cdot I_{Lh}
\]

where \( I_{Lh} \) is the load harmonic current and \( K \) is a constant.
Besides using Series APF to compensate for harmonic-voltage, it has been used to compensate negative-sequence voltage and regulate voltage in three-phase system [88].

Figure 3.2 Series APF by Singh

3.1.1.3 Unified Power Quality Conditioner

Figure 3.3 shows the system configuration of the unified power quality conditioner (UPQC). UPQC is a combination between shunt and series active power filters. The DC link VDC is common between the shunt and series APFs. It considered an Ideal Active power filter because it can compensate for both voltage
and current harmonics. The cost and control complexity are considered major drawbacks of these type of APFs [88, 91].

![Diagram of APF](image)

**Figure 3.3** Unified Power Quality Conditioner by Singh

### 3.1.1.4 Hybrid Active Power Filter

Figure 3.4 shows the main three topologies of hybrid APFs. The main purpose of introducing these types of APFs is to reduce the initial cost of shunt or series APFs [89]. The hybrid APF is a combination of passive filter (LC Filter or High pass filter) and Shunt or series APF. Usually the passive filter is tuned up to the most dominant harmonic order, which will reduce the rating needed for the APF. This will reduce the cost of the APF [89, 91].
3.1.2 Detailed Structure of Shunt Active Power Filter

Figure 3.5 shows the functional structure of shunt APF. It mainly consists of three parts [30]:

a. Power converter circuit.

b. Signal processing block, which consists of
   i. Harmonic extraction block.
   ii. Reference current calculation block.

c. PWM control block.
Whereas power converter circuit determines the cost of the shunt APF, the performance of the shunt APF is greatly depends on the signal processing and PWM control blocks.

![Shunt APF Structure](image)

**Figure 3.5 Shunt APF Structure**

### 3.1.2.1 Power Converter Topologies for Shunt APF

The power converter for shunt APF could be single phase or three phase, three-wires or four wires, and Voltage Source Converter (VSC) or Current Source Converter (CSC). Several authors talks about the comparison between the VSC and
CSC [30, 88, 92]. The VSC is more preferable because; it cost less than CSC, lighter, smaller physical size, and it has simple circuit [30, 88, 92].

3.1.2.2 Signal Processing Strategies for Shunt APF

The function of the signal processing block is to calculate the reference current needed to be realized by the power converter. The inside harmonic extraction block and reference current calculation block could be one block or separate blocks. Example, they could be on block in case of direct calculation of reference current from the load current. And they could be separate blocks in case of using transformation methods as in p-q or d-q theory. The reference current is always calculated to achieve a certain control strategy based on the goal of APF.

3.1.2.3 PWM Control

The function of the PWM control block is to force the VSC or CSC to realize the reference current with minimal error. The PWM controller will send the switching pulses to the power electronic elements in the VSC or CSC and force the power converter to act as a current source to follow the reference current changes.
3.2 Radial Basis Function Neural Networks (RBFNN)

3.2.1 Structure of RBFNN

The RBFNN structure consists mainly of three different layers as shown in figure 3.6; one input layer (source nodes with inputs $I_1$, $I_2$, ..., $I_N$), one hidden layer has $K$ neurons, and one output layer (with outputs $y_1$, $y_2$, ..., $y_m$). The input-output mapping consists of two different transformations; nonlinear transformation from the input layer to the hidden layer and linear transformation between hidden and output layers. The connection between the input and hidden layers is called centers and the connection between the hidden and output layers is called weights [7, 8].

The most common radial basis function used in RBFNN is given by

$$
\phi_i(x) = \exp \left[ -\frac{(x-c_i)^T(x-c_i)}{2\sigma_i^2} \right], \quad i=1,2,\ldots,K \quad (3.1)
$$

This is a Gaussian basis function with $\phi_i(x)$ as the output of the $i^{th}$ hidden, $x$ is the input vector data sample ($I_1$, $I_2$, ..., $I_N$) (could be training, actual, or test data), $c_i$ is centers vector of the $i^{th}$ hidden neuron ($c_{i1}$, $c_{i2}$, ..., $c_{iN}$), $\sigma_i$ is the normalization factor, and $(x-c_i)^T(x-c_i)$ is the square of the vector $(x-c_i)$ [7, 8]. The $i^{th}$ output node $y_i$ is a linear weighted summation of the outputs of the hidden layer and is given by

$$
y_i = w_i^T \Phi(x), \quad i=1,2,\ldots,m \quad (3.2)
$$
where $w_i$ is the weight vector of the output node and $\Phi(x)$ is the vector of the outputs from the hidden layer (augmented with an additional bias which assumes a value of one).

![Diagram of RBFNN Network](image)

**Figure 3.6 Structure of RBFNN Network**

### 3.2.2 Training Algorithm of RBFNN

The block diagram shown in Figure 3.7 illustrates one of the RBFNN training processes called hybrid learning process [93]. The hybrid learning process has two different stages; (i) finding suitable locations for the radial basis functions centers of the hidden neurons [8, 93] and (ii) finding the weights between the hidden and output layers. In the first stage the K-means [8, 93] clustering algorithm is used to locate the centers in the input data space regions where significant data are present (shown as I in Figure 3.7). In the second stage (shown as II in Figure 3.7) the weights between the
hidden and the output layers are found by linear matrix inversion algorithm based on the least-square solution, which minimizes the sum-squared error function [94].

![Diagram of RBFNN Hybrid Learning Process]

Figure 3.7 Block Diagram for the RBFNN Hybrid Learning Process

The weights matrix \( w \) is given by

\[
 w = A^{-1} \Phi^T D
\]

(3.3)

where \( D \) is the desired output vector for \( l \) training data samples set and given by

\[
 D = \begin{bmatrix}
 d(x_1) \\
 d(x_2) \\
 \vdots \\
 d(x_j) \\
 \vdots \\
 d(x_l)
\end{bmatrix}
\]

(3.4)

where \( d(x_j) \) describes the output vector corresponding to the \( j^{th} \) training data samples vector \( (x_j) \), \( \Phi \) is a matrix where each element \( \phi(x_j) \) (a scalar value) represents the output of the \( i^{th} \) hidden neuron for the \( j^{th} \) training data samples vector \( (x_j) \). The \( \Phi \) matrix for \( l \) training data samples is given by
A variance matrix $A^{-1}$ is computed from the $\Phi$ matrix as

$$A^{-1} = [\Phi^T \Phi]^{-1}$$  \hspace{1cm} (3.6)

One of the advantages of this method is that it does not need iterations in the training phase; what it needs is the matrix inversion shown in (3.6), which needs negligible time to be calculated.

### 3.3 Instantaneous Power Theory (p-q Theory)

Consider the three-phase controlled rectifier with R-L load as shown in Figure 3.8. A uniformly distributed random gating signal is applied to the three-phase rectifier. The voltages and currents of the rectifier are sampled and used to calculate the instantaneous active power $p$ and imaginary power $q$ based on p-q theory [30]. Clark transformation is used to transform the voltages and currents from a-b-c domain to $\alpha-\beta$ domain as shown in (3.11) and (3.12).

$$\begin{bmatrix} v_{\alpha} \\ v_{\beta} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix}$$  \hspace{1cm} (3.11)

$$\begin{bmatrix} i_{\alpha} \\ i_{\beta} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix}$$  \hspace{1cm} (3.12)
Then $p$ and $q$ are calculated from $\alpha$-$\beta$ domain voltages and current as shown in (3.13)

$$\begin{vmatrix} p \\ q \end{vmatrix} = \begin{vmatrix} v_\alpha \\ v_\beta \\ -v_\beta \\ v_\alpha \end{vmatrix} \begin{vmatrix} i_\alpha \\ i_\beta \end{vmatrix}$$

(3.13)

The instantaneous $p$ and $q$ can be decomposed into the following

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

(3.14)

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

(3.15)

where $\bar{p}$ is the constant part of $p$ (which is coming from the fundamental components), $\tilde{p}$ is the oscillating part of $p$ (which is coming from harmonics). and in similar fashion, $q$ can be decomposed into $\bar{q}$ and $\tilde{q}$.

In this dissertation, two compensation strategies have been applied [30][13]. The first is called constant power strategy. In this strategy the oscillating part of the active power $\tilde{p}$ is extracted. The resulting reference power signal contains $\bar{p}$ plus power losses ($p_{\text{loss}}$) (always present) and the total imaginary power $q$ shown as $p_{\text{ref}}$ and $q_{\text{ref}}$ in (3.16) and (3.17), respectively.
The second compensation strategy, used in this dissertation, is called *sinusoidal current* strategy. Here both oscillating parts $\bar{p}$ and $\bar{q}$ are extracted. The resulting reference power signal contains $\bar{p}$ plus $p_{\text{loss}}$ (additional power losses present) and $\bar{q}$ shown as $p_{\text{ref}}$ and $q_{\text{ref}}$ in (3.18) and (3.19), respectively.

\begin{align}
p_{\text{ref}} &= \bar{p} + p_{\text{loss}} \quad (3.16) \\
q_{\text{ref}} &= q = \bar{q} + \bar{q} \quad (3.17)
\end{align}

In real world, the constant part $\bar{q}$ will be compensated by a conventional power factor correction capacitor or condenser.

The reference current in $\alpha$-$\beta$ domain can be calculated by

\[
\begin{bmatrix}
i_{\text{aref}} \\
i_{\beta\text{ref}}
\end{bmatrix} = \begin{bmatrix} v_\alpha & v_\beta \\ -v_\beta & v_\alpha \end{bmatrix}^{-1} \begin{bmatrix} p_{\text{ref}} \\ q_{\text{ref}} \end{bmatrix} \quad (3.20)
\]

Then the reference current in $a$-$b$-$c$ domain can be calculated

\[
\begin{bmatrix}
i_{\text{aref}} \\
i_{\beta\text{ref}} \\
i_{\text{cref}}
\end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \frac{-1}{2} & \frac{\sqrt{3}}{2} \\ \frac{-1}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} i_{\text{aref}} \\ i_{\beta\text{ref}} \\ i_{\text{cref}} \end{bmatrix} \quad (3.21)
\]
3.3.1 Example

Consider a three-phase system with sinusoidal balanced voltage and balanced nonlinear load as following

\[ v_a(t) = \sqrt{2} V \sin(wt) \]
\[ v_b(t) = \sqrt{2} V \sin\left(wt - \frac{2\pi}{3}\right) \]
\[ v_c(t) = \sqrt{2} V \sin\left(wt + \frac{2\pi}{3}\right) \]

\[ i_a(t) = \sqrt{2} i_1 \sin(wt - \theta_1) - \sqrt{2} i_5 \sin(5wt - \theta_5) + \sqrt{2} i_7 \sin(7wt - \theta_7) \]
\[ i_b(t) = \sqrt{2} i_1 \sin\left(wt - \frac{2\pi}{3} - \theta_1\right) - \sqrt{2} i_5 \sin\left(5wt + \frac{2\pi}{3} - \theta_5\right) + \sqrt{2} i_7 \sin\left(7wt - \frac{2\pi}{3} - \theta_7\right) \]
\[ i_c(t) = \sqrt{2} i_1 \sin\left(wt + \frac{2\pi}{3} - \theta_1\right) - \sqrt{2} i_5 \sin\left(5wt - \frac{2\pi}{3} - \theta_5\right) + \sqrt{2} i_7 \sin\left(7wt + \frac{2\pi}{3} - \theta_7\right) \]

Using (3.11) and (3.12) the voltage and current in \(\alpha-\beta\) domain values can be calculated as

\[ v_a(t) = \sqrt{3} V \sin(wt) \]
\[ v_b(t) = -\sqrt{3} V \cos(wt) \]
\[ i_a(t) = \sqrt{3} i_1 \sin(wt - \theta_1) - \sqrt{3} i_5 \sin(5wt - \theta_5) + \sqrt{3} i_7 \sin(7wt - \theta_7) \]
\[ i_b(t) = \sqrt{3} i_1 \cos(wt - \theta_1) - \sqrt{3} i_5 \cos(5wt - \theta_5) + \sqrt{3} i_7 \cos(7wt - \theta_7) \]
The instantaneous $p$ and $q$ are calculated from (3.13) as

$$p(t) = 3VI_{1}\cos(\theta_1) - 3VI_5\cos(4wt - \theta_5) + 3VI_7\cos(6wt - \theta_7)$$

$$q(t) = 3VI_{1}\sin(-\theta_1) - 3VI_5\sin(4wt - \theta_5) + 3VI_7\sin(6wt - \theta_7)$$

It is clear that both $p$ and $q$ have two parts; constant parts ($\bar{p}$ and $\bar{q}$) and oscillating parts ($\tilde{p}$ and $\tilde{q}$). Where

$$\bar{p} = 3VI_{1}\cos(\theta_1)$$

$$\bar{q} = 3VI_{1}\sin(-\theta_1)$$

$$\tilde{p} = -3VI_5\cos(4wt - \theta_5) + 3VI_7\cos(6wt - \theta_7)$$

$$\tilde{q} = 3 - 3VI_5\sin(4wt - \theta_5) + 3VI_7\sin(6wt - \theta_7)$$

The reference values are then computed from (3.20) and (3.21).
CHAPTER 4

HARMONICS EXTRACTION

4.1 Introduction

Assume a load current signal \( I_L \) can be expressed by Fourier series as

\[
I_L = A_1 \sin(\omega t + \theta_1) + \sum_{n=1}^{\infty} A_n \sin(w_n t + \theta_n) \quad (4.1)
\]

\[
I_L = A_1 \cos \theta_1 \sin(\omega t) + \{A_1 \sin \theta_1 \cos(\omega t) + \sum_{n=1}^{\infty} A_n \sin(w_n t + \theta_n)\} \quad (4.2)
\]

where

\( A_1 \cos \theta_1 \sin (\omega t) \) is the active fundamental current.

\( A_1 \sin \theta_1 \cos(\omega t) \) is the reactive fundamental current.

\( \sum_{n=1}^{\infty} A_n \sin(w_n t + \theta_n) \) is total harmonics current.

The Harmonic extraction problem is centered on how to separate the active fundamental current from other components. These components can be varying based on the control strategies. These strategies include:

- The extraction of total harmonics without the reactive fundamental current (sinusoidal current strategy).
- The extraction of total harmonic and reactive fundamental current.
- The selective harmonic extraction.

In this dissertation three different methodologies are used to extract the harmonics components:
i. Combine the RBFNN and p-q theory for total harmonic extraction.

ii. Use multi-input-multi-output (MIMO) RBFNN for selective harmonic extraction directly from the load current.

iii. Novel adaptive RBFNN for total harmonic extraction directly from the load current.

4.2 RBFNN and p-q Power Theory Based for Total Harmonic Identification in Converter Waveforms

4.2.1 RBFNN Method

4.2.1.1 Building the Delay Buffer

Figure 4-1 shows an example of instantaneous active power waveform. Data are sampled at constant rate and passed through first-input-first-output (FIFO) buffer to create a delayed vector with length $N$, which match the length of the input vector of the RBFNN.
At any instant the FIFO buffer will contain $N$ data samples. As an illustration for the building of the FIFO buffer, the first training data sample $x_1$ is given by

$$x_1 = \begin{bmatrix} p_{11} = p_1 \\ p_{21} = 0 \\ \vdots \\ p_{N1} = 0 \end{bmatrix} \quad (4.3)$$

The second training data sample $x_2$ is given by

$$x_2 = \begin{bmatrix} p_{12} = p_2 \\ p_{22} = p_1 \\ 0 \\ \vdots \\ p_{N1} = 0 \end{bmatrix} \quad (4.4)$$

And the $j^{th}$ training data sample is given by
The \( l \) training data samples is written in matrix form as \( X \)

\[
X = \begin{bmatrix}
  x_1 & x_2 & \cdots & x_l
\end{bmatrix}
\]

\[
= \begin{bmatrix}
p_{1j} & p_{j-1} & \cdots & p_{j-N+1}
\end{bmatrix}
\]

The \( l \) training data samples is written in matrix form as \( X \)

\[
p_{1j} = p_j
\]
\[
p_{2j} = p_{j-1}
\]
\[
\vdots
\]
\[
p_{Nj} = p_{j-N+1}
\]

4.2.1.2 Finding the Desired Output

For each \( x_j \), the fast Fourier transform (FFT) is used to find the constant (DC) part of the active power (which represents the power due to the fundamental components). The constant part obtained from applying the FFT on \( x \)'s data become the desired output that mentioned in (3.4)

\[
FFT\{x_j\} = d_j^{DC}
\]

Note that only the DC component of the FFT is taken, which is a scalar quantity, not a vector as generalized by (3.4) since the number of the output nodes is one. The desired output vector obtained from the applying FFT on each \( x_j \) is given by
The training data samples matrix $X$ of (4.6) is the same data used by the K-means clustering algorithm to find the centers vectors ($c_1$, $c_2$, ..., $c_K$) used in (3.1). The Gaussian radial basis function of (3.1) is then used to find the matrix $\Phi$ of the hidden neurons outputs. The weights vector $w$ then can be found using (3.3).

4.2.1.3 Embedding RBFNN Model in the System

After obtaining the RBFNN model parameters (centers and weights) from the training process, the RBFNN model now is ready to be tested. Generally there are two different stages of testing; recalling and generalization testing. The recalling process includes applying the same training data as a test signal for the resulted RBFNN network. The generalization test includes applying new data never been seen before by the neural network model. The test is performed by embedding the RBFNN model in environment that can apply a delayed power vector as an input for RBFNN model. Then compare the output from RBFNN model with the actual output.

Back to the example in section 3.4.1, the following power signal is obtained from the system:

$$D = \begin{bmatrix} d_1^{dc} \\ \vdots \\ d_j^{dc} \\ \vdots \\ d_L^{dc} \end{bmatrix}$$ (4.8)
\[ p(t) = 3V I_1 \cos(\theta_1) - 3V I_5 \cos(4wt - \theta_5) + 3V I_7 \cos(6wt - \theta_7) \]

To make such a signal suitable for RBFNN model, this signal should be sampled at the same constant rate used in the training phase. Then a delayed vector should be constructed in the same way illustrated in section 4.1.1.1. An example of the input vector will be as

\[
x_k = \begin{bmatrix}
p_{1k} \\
p_{2k} \\
\vdots \\
p_{Nk}
\end{bmatrix}
\]

Once the delayed vector is obtained, the output of RBFNN model can be calculated based on (3.1) and (3.2) to obtain the RBFNN output \( y_k \). The output \( y_k \) is compared with actual output \( \bar{p}(k) \) and the oscillating part can be easily found by

\[
\bar{p}(k) = p(k) - \bar{p}(k)
\]

### 4.2.2 Simulation Results

The three-phase nonlinear load has the following parameters:

**Voltage Source** 400 V L-L, 60 Hz, source resistance 0.06 mΩ, source inductance 2 µH

**Nonlinear Load** Three-Phase thyristor rectifier with R-L load (450 kW active power, 200 kVAR reactive power)

**Sampling Rate** 128 sample/cycle
RBFNN for p  
2 Hidden neurons, sigma (σ) = 71.5

RBFNN for q  
4 Hidden neurons, sigma (σ) = 42.5

The value of σ depends on the input training data. This value was obtained by running the simulation several times and selecting the value that minimizes the RBFNN network error.

4.2.2.1 Constant Active Power Extraction

Figure 4.2(a) shows a window from the training set for the active power obtained by the algorithm illustrated in Section III. In this training set the input for the RBFNN network is the delayed vectors of the total active power (N=64), which is calculated based on the p-q theory. Figure 4.2 (b) shows the desired output, which is the DC component of the delayed vector. Figure 4.3 shows the performance of the network for the recalling process. The mean square error for the recalling process for the p-RBFNN is 1.49*10^-7 for normalized data.
Figure 4.2 Window of Training Data for the Active Power RBFNN Network
The p-RBFNN network model is tested by embedding the models inside a nonlinear SIMULINK® model. The RBFNN is used to extract the DC component of the active power, consumed by a three-phase thyristor-rectifier with a R-L load. The total active power is shown in Figure 4.4(a). It is clear that it has two components; a DC part, due to fundamental components, and an oscillating part, due to the harmonic content of the load current. Figure 4.4 (b) shows the output of the embedded RBFNN network, which is the DC part of the active power, with a minor ripple. The oscillating parts of the active power are obtained by subtracting the DC part from the total part as shown in Figure 4.4 (c). Figure 4.5 shows the FFT analysis of the active power waveforms shown in Figure 4.4. These results emphasize the robustness of the RBFNN network in decomposing the active power waveform.
Figure 4.4 Active Power Consumed by the Three-Phase Rectifier (a) Total (b) DC Part (c) Oscillating Part
4.2.2.2 Constant Imaginary Power Extraction

Using a method similar to the one used for the active power, the imaginary power is decomposed into two parts; a DC part and an oscillating part using another RBFNN model. Figure 4.6(a) shows a window from the training set for the imaginary power. In this training set the input for the RBFNN network is the delayed vectors of the total
imaginary power (N=64). Figure 4.6 (b) shows the desired output, which is the DC component of the delayed vector. Figure 4.7 shows the performance of the network for the recalling process. The mean square error of the recalling process for the q-RBFNN is $1.12 \times 10^{-5}$ for normalized data.

Figure 4.6 Window of Training Data for the Imaginary Power RBFNN Network
CHAPTER I

The q-PRBFNN is used to extract the DC component of the imaginary power, consumed by a thyristor rectifier with a R-L load. The total active power is shown in Figure 4.8 (a). It is clear that it has two components; a DC part, due to the fundamental components, and an oscillating part, due to the harmonic content of the load current. Figure 4.8 (b) shows the output of the embedded RBFNN network, which is the DC part of the active power, with a minor ripple. The oscillating parts, of the active power are obtained by subtracting the DC part from the total part as shown in Figure 4.8 (c). Figure 4.9 shows the FFT analysis for the active power waveforms shown in Figure 4.8. The results emphasize the robustness of the q-RBFNN network in decomposing the imaginary power waveform.
Figure 4.8 Imaginary Power Exchanged between the Phases (a) Total (b) DC Part (c) Oscillating Part
Figure 4.9 FFT for the Imaginary Power Signals in Figure 10 (a) Total (b) DC Part (c) Oscillating Part

4.2.2.3 Constant Power Strategy

Figures 4.10 and Figure 4.11 show the results of applying the constant power strategy. Figure 4.10 (a) shows phase $A$ source current before compensating and Figure 4.10(b) shows the compensating signal (reference current). The compensating signal is added to the source current as an output from active power filter, and the
result is shown in Figure 4.10(c). It is clear that the source current does not contain harmonics because it is pure sinusoidal.

Figure 4.10 Phase A Source Current for Constant Power Strategy (a) Before Compensation (b) Reference Current (c) After Compensating

Figure 4.11(a) shows the source active power and Figure 4.11(b) shows the source imaginary power. It is clear from Figure 4.11 that the source delivers only constant active power after the filter is ON.
4.2.2.4 Sinusoidal Current Strategy

Figure 4.12 and Figure 4.13 show the results of applying the sinusoidal current strategy. Figure 4.12 (a) shows phase $A$ source current before compensating and Figure 4.12(b) shows the compensating signal (reference current). This signal is
added to the source current as an output from active power filter and the result is shown in Figure 4.12(c). Figure 4.13(a) shows the Source active power and Figure4.13 (b) shows the source imaginary power.

Figure 4.12 Phase A Source Current for Sinusoidal Current Strategy (a) Before Compensation (b) Reference Current (C) After Compensating
The major difference between the two methods is that the active power filter in the first case needs to compensate for the oscillating part of the active power and the whole imaginary power, resulting in a constant source active power, with currents that are in-phase with the supply voltages. In the second case, the active filter needs to compensate only for the oscillating parts of the active and imaginary powers, resulting in sinusoidal source currents that are not in-phase with the source voltages.

Figure 4.13 Source Power for Sinusoidal Current Strategy (a) Active Power (b) Imaginary Power
4.2.2.5 Disturbance Rejection

Disturbance rejection robustness of RBFNN network is investigated by step changing the firing angle of Thyristor bridge, which will change the harmonics content level. Figure 4.14 shows the response of the active power RBFNN network for this change. Figure 4.14 shows the fast response to this change (around half a cycle) and the absence of overshoot. Figure 4.15 shows the response of the imaginary power RBFNN network for this change. The smooth transition reflects the robustness of the RBFNN to reject the disturbance.

Figure 4.14 RBFNN Network Response for a Firing Angle Step Change from 10° -20°. DC Power (Dashed), Oscillating Power (Solid)
Figure 4.15 RBFNN Network Response for a Firing Angle Step Change from $10^\circ$ - $20^\circ$ (a) DC Imaginary Power (b) Oscillating Imaginary Power
4.3 On-Line Harmonic Estimation in Power System Based on Sequential Training Radial Basis Function Neural Network

4.3.1 RBFNN for Selective Harmonic Estimation

Consider the three-phase controlled rectifier with R-L load as shown in Figure 3.8. The input current (source), that contains harmonics, is sampled at constant rate. These sampled data are used to create the training data for the RBFNN which consist of input training data (delay buffer) and desired output data. The RBFNN training algorithm uses the training data to adjust its parameters in order to minimize the error between the outputs of the RBFNN and the desired outputs. In this dissertation the fundamental, fifth, and seventh harmonic components are identified using MIMO RBFNN model.

4.3.1.1 Building the Delay Buffer (Input Training Data)

Figure 4.16 shows a window of phase A source current waveform. Sampled at constant rate and passed through FIFO buffer to create a delayed vector with length N, which match the length of the input vector of RBFNN. At any instant the FIFO buffer will contain N data samples.
As an illustration for the building of the FIFO buffer, the first training data sample $x_1$ is given by

\[
x_1 = \begin{bmatrix}
i_{11} = i_1 \\
i_{21} = 0 \\
\vdots \\
i_{N1} = 0
\end{bmatrix}
\]  \tag{4.9}

The second training data sample $x_2$ is given by

\[
x_2 = \begin{bmatrix}
i_{12} = i_2 \\
i_{22} = i_1 \\
0 \\
\vdots \\
i_{N1} = 0
\end{bmatrix}
\]  \tag{4.10}

And the $j^{th}$ training data sample is given by

\[
x_j = \begin{bmatrix}
i_{1j} = i_j \\
i_{2j} = i_{j-1} \\
\vdots \\
i_{Nj} = i_{j-N-1}
\end{bmatrix}
\]  \tag{4.11}

The $l$ training data samples is written in matrix form as $X$
4.3.1.2 Finding the Desired Output

Fast Fourier transform (FFT) is applied, on several fundamental cycles of source current waveform, to estimate the actual magnitude and the phase of the fundamental, fifth, and seventh harmonic components. These harmonics are used as the desired output vectors for the RBFNN.

The desired output matrix for \( l \) training sample obtained from the applying FFT is given by

\[
D = \begin{bmatrix}
    d_{1h1} & d_{1h5} & d_{1h7} \\
    d_{2h1} & d_{2h5} & d_{2h7} \\
    \vdots & \vdots & \vdots \\
    d_{lh1} & d_{lh5} & d_{lh7}
\end{bmatrix}
\]  

where \( d_{1h1} \) represents the fundamental desired output for the first training data vector, \( d_{1h5} \) represents the fifth harmonic desired output for the first training data vector, and \( d_{1h7} \) represents the seventh harmonic desired output for the first training data vector.

The training data samples matrix \( X \) of (4.12) is the same data used by the K-means clustering algorithm to find the centers vectors \( (c_1, c_2, \ldots, c_K) \) used in (3.1). The Gaussian radial basis function of (3.1) is then used to find the matrix \( \Phi \) of the hidden neurons outputs. The weights vector \( w \) can be found using (3.3).
4.3.2 Simulation Results

Voltage Source 400 V L-L, 60 Hz, source resistance 0.06 mΩ, source inductance 2 μH

Nonlinear Load Three-Phase thyristor rectifier with R-L load (450 kW active power, 200 kvar reactive power)

Sampling Rate 128 sample/cycle

RBFNN for p 2 Hidden neurons, sigma (σ) = 71.5

RBFNN for q 4 Hidden neurons, sigma (σ) = 42.5

The current signal of the three phase thyristor rectifier SIMULINK® model is used to verify the capability of the RBFNN to identify the first, the fifth, and the seventh harmonic component. The number of the hidden neuron was chosen to be 9. Figure 4.17 shows the phase \(A\) current and its harmonic contents. Figures 4.18, 4.19, and 4.20 show the performance of RBFNN for estimating the fundamental, fifth harmonic, and the seventh harmonic components respectively.
Figure 4.17 Phase A Source Current (firing angle=15°) (a) and its Harmonic Content (b)
Figure 4.18  Fundamental Desired Output (solid) and RBFNN Output (dashed) (a) Actual-Estimated (b) NMSE = 3.6*10^{-4}
Figure 4.19 Fifth Harmonic Desired Output (solid) and RBFNN Output (dashed) (a) Actual-Estimated (b) NMSE=0.0020
Figure 4.20 Seventh Harmonic Desired Output (solid) and RBFNN Output(dashed) (a) Actual-Estimated (b) NMSE=0.0164

Table 1 shows the effect of changing the number of hidden neurons on the RBFNN performance. In general, as the number of hidden neurons increases, the identification errors decrease. As the number of hidden neuron increases, the separability in the
hidden space increases. But there must be a compromise, because as the number of hidden neurons increases, the overhead computations also increase, which is a very important consideration in real-time applications.

Table 4.1 Effect of the Numbers of Hidden Neurons (sigma=230)

<table>
<thead>
<tr>
<th># of Hidden Neurons</th>
<th>Fundamental (NMSE)</th>
<th>Fifth Harmonic (NMSE)</th>
<th>Seventh Harmonic (NMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>3.6*10^{-4}</td>
<td>0.0020</td>
<td>0.0164</td>
</tr>
<tr>
<td>13</td>
<td>3.48*10^{-4}</td>
<td>0.0016</td>
<td>0.0034</td>
</tr>
<tr>
<td>19</td>
<td>3.76*10^{-4}</td>
<td>0.0022</td>
<td>0.0023</td>
</tr>
</tbody>
</table>

Table 2 shows the effect of changing the length of the delayed input vector (represents a percentage of the fundamental harmonic waveform. For example a 32 input vector length in Table 2 represents a quarter of the fundamental harmonic waveform). In general, as the length of the delayed input vector increases, the identification errors decrease. There must also be a compromise, because as the length of the delayed input vector increases, the overhead computations also increase, which is a very important consideration in real-time applications.

Table 4.2 Effect of Delayed Input Vector Length (hn=13, Sigma=230)

<table>
<thead>
<tr>
<th>Length of window</th>
<th>Fundamental (NMSE)</th>
<th>Fifth Harmonic (NMSE)</th>
<th>Seventh Harmonic (NMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>0.0012</td>
<td>0.0468</td>
<td>0.0573</td>
</tr>
<tr>
<td>64</td>
<td>3.48*10^{-4}</td>
<td>0.0016</td>
<td>0.0034</td>
</tr>
<tr>
<td>128</td>
<td>3.01*10^{-4}</td>
<td>0.0023</td>
<td>0.0025</td>
</tr>
</tbody>
</table>
Table 3 shows comparison between the performance errors for K-mean and C-mean clustering algorithms. Table 3 shows the superiority of using K-means clustering algorithm in the situations where the harmonic magnitude is significant. But as the harmonic magnitude decreases (as in the seventh harmonic), the C-means algorithm shows less performance error.

Table 4.3 Effect of Clustering Algorithm (sigma=230)

<table>
<thead>
<tr>
<th>Estimated signal</th>
<th>K-Mean Clustering</th>
<th>Fuzzy C-Mean Clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamental (Hn=9)</td>
<td>3.6*10⁻⁴</td>
<td>5.68*10⁻⁴</td>
</tr>
<tr>
<td>Fifth Harmonic (Hn=9)</td>
<td>0.0020</td>
<td>0.0019</td>
</tr>
<tr>
<td>Seventh Harmonic (Hn=9)</td>
<td>0.0164</td>
<td>0.0094</td>
</tr>
<tr>
<td>Fundamental (Hn=13)</td>
<td>3.48*10⁻⁴</td>
<td>5.6619e-004</td>
</tr>
<tr>
<td>Fifth Harmonic (Hn=13)</td>
<td>0.0016</td>
<td>0.0029</td>
</tr>
<tr>
<td>Seventh Harmonic (Hn=13)</td>
<td>0.0034</td>
<td>0.0025</td>
</tr>
</tbody>
</table>

The acceptable error for implementation depends on particular application. The standard IEEE-519 specifies different acceptable harmonic distortion limits based on the maximum short circuit current to the maximum load current ratios. Until now no benchmark data and error standards are available.
4.4 Adaptive RBFNN for Estimation of Fundamental Component of Nonlinear Load Current

4.4.1 Novel Adaptive Algorithm for RBFNN

One of the major disadvantages of the feedforward neural networks (BPNN and RBFN) techniques is the parameters obtained do not changed once the training process is completed. In the presence of the noise, these fixed parameters can degrade the performance of the neural networks. The main objective of this algorithm is to enhance the reliability of the RBFNN after embedding the network in the system. This can be achieved by introducing an algorithm for RBFNN structure that allows the change of the weights of RBFNN after the training process is completed. This algorithm assumes that the noise present in the system will not affect the input space and therefore no need to change the RBFNN centers values.

Figure 4.21 illustrates the principle of the adaptation process after embedding the RBFNN model in the system. In the absence of the noise \( \delta(k) \) in the input side, the summation of the outputs of the RBFNN model is equal to the reference signal \( R(k) \). In this case the error \( E(k) \) equal to zero and no change in the RBFNN weights.

\[
E(k) = R(k) - \{y_1(k) + y_2(k) + \cdots + y_m(k)\} \quad (4.14)
\]

In the presence of noise in the input side, the \( j^{th} \) output node of the RBFNN will be affected by this noise as

\[
y_j(k) = y_{ojj}(k) + \delta_j(k) \quad (4.15)
\]
where \( y_{o_j}(k) \) is the \( j^{th} \) output node without noise and \( \delta_j(k) \) is the added noise error to the \( j^{th} \) output node.

In this case the error \( E(k) \) is not equal to zero.

In order to mitigate the effect of the noise in the performance of the RBFNN, the error \( E(k) \) is used to update the weights vectors based on the least-mean-square-error algorithm [7] as:

\[
w_{n_{ew}} = w_{n_{old}} + \eta \varphi(k)E(k) \quad (4.16)
\]

Figure 4.21 Structure of the Adaptive RBFNN Algorithm
\[ w_{mn_{new}} = w_{mn_{old}} + \eta_m \phi(k)E(k) \quad (4.17) \]

where \( \eta_1 \) is the regulation factor for the \( j^{th} \) output node.

The weights updating will continue until the error \( E(k) \) become zero again.

The above algorithm has several advantages including the following:

- It has a fast convergence time because it adjusts only the weights between the hidden and output layers, which is a linear relationship. Therefore, fast convergence can be achieved.
- The updating process could be initiated based on threshold value for \( E(k) \) (different from zero), which gives the flexibility to the algorithm and saves excessive computations.
- This algorithm has greater capabilities compare to the popular neural linear adaptive algorithm (ADALINE) because, the RBFNN structure can be used to realize linear and nonlinear functions.

### 4.4.2 Adaptive RBFNN for Estimation of Fundamental Component of Nonlinear Load Current

Figure 4.22 shows the block diagram of the proposed algorithm. The proposed algorithm will be used to extract the fundamental component from a noisy source current of a three-phase controlled rectifier with R-L load (as shown in Figure 3.8). The input current (source), that contains harmonics, is sampled at constant rate. These sampled data are used to create the input training data for the RBFNN which consists
of a delay buffer as in Section 4.1.3.1.1. The desired output data (fundamental component and the harmonics component) are obtained by applying the \( p-q \) theory as used in Section 4.1.12.2. The proposed algorithm uses The RBFNN training algorithm, as used in the Sections 4.1.1 and 4.1.2, to obtain its parameters. The proposed algorithm will allow the weights, between the hidden layer and the output layer, to be modified after the end of the training phase. If the error between the reference current and the estimated signal (the sum of the fundamental and the harmonics components) exceeds a predetermined threshold, the algorithm will try to minimize the error caused by the noise signal \( (\delta) \) as:

\[
\begin{align*}
  w_{1\text{new}} &= w_{1\text{old}} + \eta_1 \varphi(k)E(k) \\
  w_{h\text{new}} &= w_{h\text{old}} + \eta_h \varphi(k)E(k)
\end{align*}
\]

where \( w_f \) is the weight vector between the hidden and the output layers for the fundamental output, \( w_h \) is the weight vector between the hidden and the output layers for the harmonics content output, \( \varphi(k) \) is the \( k^{th} \) output vector of the hidden layer, \( \eta_1 \) is the regulation factor for the estimated fundamental output, \( \eta_h \) is the regulation factor for the estimated harmonics content output, and \( E(k) \) is the \( k^{th} \) error between the reference signal \( (I_f(k)) \) and the estimated signal \( (I_f(k) + I_h(k)) \).
4.4.2.1 Example

To illustrate the proposed adaptive RBFNN algorithm; the following numerical example shows how the proposed algorithm updates the weights between the hidden and the output layers for a given scenario.

Assume the following RBFNN networks used to estimate the fundamental current and the harmonics current with the following scenario:

Hidden neurons number = 5, output number = 2, the hidden layer output vector \( \phi(k) = [2, -3, 6, -1, 4] \), the weights between the hidden and output layers for the estimated fundamental current \( w_{1old} = [9, 2, 0.5, -2, 7]^T \), the weights between the hidden and
output layers for the estimated harmonics current $w_{hold}=[1, 0.02, 0.4, -0.3 0.8]^T$, the total reference current $I_{ref}(k)=55A, \eta_1=0.015, \eta_h=0.001$

The estimated fundamental current, $I_f(k) = \phi(k)*w_{1old}$

$$=[2, -3, 6, -1, 4]*[9, 2, 0.5, -2, 7]^T=45A$$

The estimated harmonics current $I_h(k) = \phi(k)*w_{hold}$

$$=[2, -3, 6, -1, 4]*[1, 0.02, 0.4, -0.3 0.8]^T=7.84A$$

The total estimated current $I_{act}(k)=I_f(k)+I_h(k)=45+7.84=52.84A$

The error between the reference and the estimated currents, $E(k) = I_{ref}(k) - I_{act}(k)$

$$=55-52.84=2.16 A.$$ The error $E(k)$ is used to update the weights ($w_{1old}$ and $w_{hold}$) as:

$$w_{1new} = w_{1old} + \eta_1 \phi(k)E(k)$$

$$=[9, 2, 0.5, -2, 7]^T + 0.015*[2, -3, 6, -1, 4]^T*2.16$$

$$=[9.0648, 1.9028, 0.6944, -2.0324, 7.1296]^T$$

$$w_{hnew} = w_{hold} + \eta_h \phi(k)E(k)$$

$$=[1, 0.02, 0.4, -0.3 0.8]^T + 0.001*[2, -3, 6, -1, 4]^T*2.16$$

$$=[1.0648, -0.0772, 0.5944, -0.3324, 0.9296]^T$$

The new values of the estimated fundamental and harmonics currents are:
\[ I_{\text{new}}(k) = \phi(k) * w_{\text{new}} = [2, -3, 6, -1, 4] * [9.0648, 1.9028, 0.6944, -2.0324, 7.1296]^T = 47.13 \ A \]

\[ I_{\text{hnew}}(k) = \phi(k) * w_{\text{hnew}} = [2, -3, 6, -1, 4] * [1.0648, -0.0772, 0.5944, -0.3324, 0.9296]^T = 7.98 \ A \]

The new total estimated current \( I_{\text{act}}(k) = I_{\text{new}}(k) + I_{\text{hnew}}(k) = 47.13 + 7.98 = 55.11 \ A \)

It is clear from this example that the proposed algorithm can reduce the error between the reference and the estimated currents.

4.4.3 Simulation Results

The system was built using MATLAB/SIMULINK with the following parameters:

- **Voltage Source**: 400 V L-L, 60 Hz, source resistance 0.06 mΩ, source inductance 2 µH
- **Nonlinear Load**: Three-Phase thyristor rectifier with R-L load (450 kW active power, 200 kvar reactive power)
- **Sampling Rate**: 128 sample/cycle
- **RBFNN**: 9 Hidden neurons, sigma (\( \sigma \)) = 290
- \( \eta_1, \eta_h \): 0.015951, 0.00015 respectively
The performance of the proposed algorithm was investigated by comparing its performance with the performance of the conventional RBFNN, similar to the used one in Section 4.1.2. The performance of the two algorithms is investigated under different cases and different types of noises. Figure 4.23 shows the performance of the Adaptive RBFNN algorithm and the RBFNN algorithm without a noise signal. The MSE for estimating the current source is the same for the both algorithms.

Figure 4.23 Estimated Source Current without Noise Signal: Reference (Solid), Adaptive RBFNN (Dashed, MSE=0.0013), and RBFNN (Dotted, MSE=0.0013)
Figure 4.24 shows the first noise signals was applied on the input of the RBFNN system. It represents another nonlinear load that has the same signal characteristics. Figure 4.25 and Figure 4.26 show the superiority of the adaptive RBFNN over the conventional RBFNN to mitigate the effect of the noise signal. In Figure 4.25 the adaptive RBFNN shows the ability to estimate the source current with small error (MSE= 0.0057) compare to the conventional RBFNN (MSE= 0.0396). Also the proposed algorithm can estimate the fundamental components of the source current more accurately as shown in Figure 4.26.

Figure 4.24 Same Nonlinear Load Noise Signal (Signal= 0.25 * Source current)
Figure 4.25 Estimated Source Current with Nonlinear Load Noise Signal: Reference (Solid), Adaptive RBFNN (Dashed, MSE= 0.0057), and RBFNN (Dotted, MSE= 0.0396)

Figure 4.27 shows the second noise signals was applied on the input of the RBFNN system. It represents a linear load connected to the same bus. Figure 4.28 and Figure 4.29 show the ability of the adaptive RBFNN to minimize the effect of this noise signal.
Figure 4.26 Estimated Fundamental Component of the Source Current with Nonlinear Load Noise Signal: Reference (Solid), Adaptive RBFNN (Dashed, MSE= 0.003), and RBFNN (Dotted, MSE= 0.03)

Figure 4.27 Linear Load Noise Signal (Signal= 200*sin (2\Pi *60*t))
Figure 4.28 shows the performance of both adaptive RBFNN (MSE= 0.003) and the conventional RBFNN (MSE= 0.033) for estimating the source current, under a sinusoidal-noise signal. Figure 4.29 shows the performance of both algorithms to estimate the fundamental component under the same sinusoidal-noise signal. It is clear from both figures that the adaptive RBFNN is more impressive in minimizing the sinusoidal-noise signal effect.

Figure 4.28 Estimated Source Current with Linear Load Noise Signal: Reference (Solid), Adaptive RBFNN (Dashed, MSE= 0.003), and RBFNN (Dotted, MSE= 0.033)
Figure 4.29 Estimated Fundamental Component of the Source Current with Linear Load Noise Signal: Reference (Solid), Adaptive RBFNN (Dashed, MSE = 0.002), and RBFNN (Dotted, MSE = 0.025)

Figure 4.30 shows the final noise signals was applied on the input of the RBFNN system. It is a white Gaussian noise signal and represents a measurement error noise signal. Figure 4.31 shows that both adaptive RBFNN and conventional RBFNN can effectively mitigate this type of noise signals.
Figure 4.30 White Gaussian Noise Signal

Figure 4.31 Estimated Source Current with Linear Load Noise Signal: Reference (Solid), Adaptive RBFNN (Dashed, MSE= 0.0013), and RBFNN (Dotted, MSE= 0.0013)
CHAPTER 5

A NOVEL ADAPTIVE HYSTERESIS CURRENT CONTROLLER WITH USER-DEFINED SWITCHING FREQUENCY FOR SHUNT ACTIVE POWER FILTER (SAPF)

5.1 Introduction

The purpose of the SAPF is to remove the harmonics components from the source current so that the system will draw a sinusoidal current. The precise and fast control algorithms are required in order to achieve the sinusoidal current. Literature contains many algorithms are used to drive the SAPF circuit [47, 49, 72, 88, 89, 95-97]. The hysteresis current control (HCC) algorithm is considered the most suitable algorithm because it is fast, easy to implement, accurate, and unconditionally stable [10, 11]. The conventional HCC algorithm has a few drawbacks such as variable switching frequency and interference between phases in three phase case [12-16]. Several papers tried to tackle the variation of the switching frequency for the HCC algorithm, but many of these papers end up with control algorithms that complicate the HCC algorithms and make it lose its simplicity [11, 66]. This dissertation introduces a novel, effective, and easy to implement control algorithm for the HCC. This algorithm is a user defined switching frequency and depends on comparing the actual switching frequency with a reference switching frequency, then update the hysteresis band based on the sign and the value of the difference between the switching and the reference frequencies.
5.2 Conventional HCC Algorithm

Figure 5.1 shows how the conventional HCC algorithm works. It depends on the current error ($\Delta I$) between the reference current ($I_c^*$) and the actual current ($I_c$); if this difference exceeds any boundary of the hysteresis band the switching state will be toggled as following:

If $I_c < I_c^* - HB$ ($\Delta I > HB$) $Output = 1$ (ON)

If $I_c > I_c^* + HB$ ($\Delta I < -HB$) $Output = 0$ (OFF)

The switching period ($T$) is given by:

$$T = T_{ON} + T_{OFF}$$

where $T_{ON}$ is the time while the switch is on and $T_{OFF}$ is the time while the switch is off.

Also, The switching frequency ($F_S$) is given:

$$F_S = \frac{1}{T}$$
Figure 5.1 Conventional Hysteresis Current Control Algorithm
In conventional HCC two successive switching period are not necessary equal. This inequality in the switching periods is happened because of the rising and the falling slope of $I_c$ are depend on the system parameters and also can be affected by the other phases interference in the case of three-phase systems. Those reasons make the conventional HCC suffer from variable switching frequency.

**5.3 Switching Frequency - Hysteresis Band Relationship**

In order to derive the relation between the hysteresis band and switching frequency the power circuit of the SAPF shown in Figure 5.2 (a) has been adopted. The SAPF is assumed to be connected to a balanced three phase system as shown in Figure 5.2 (a). The switching transistors $T_1$ to $T_6$ are supposed to be driven by a HCC unit.

From Figure 5.2 (b), by applying the Kirchhoff’s voltage law the following equation can be obtained:

$$ V_{fa} = V_{f1} + V_{SN} $$

Similarly, for the phases $b$ and $c$

$$ V_{fb} = V_{f2} + V_{SN} \quad \quad (5.1) $$

$$ V_{fc} = V_{f3} + V_{SN} $$

Taking into the account the balance three-phase system in (5.1), the S-point-to-neutral voltage is given by summing (5.1) as:

$$ V_{SN} = -\frac{1}{3}(V_{f1} + V_{f2} + V_{f3}) \quad \quad (5.2) $$
Substitute (5.2) into (5.1)

\[ V_{fa} = \frac{2}{3} V_{f1} - \frac{1}{3} V_{f2} - \frac{1}{3} V_{f3} \]

\[ V_{fb} = -\frac{1}{3} V_{f1} + \frac{2}{3} V_{f2} - \frac{1}{3} V_{f3} \]  \hspace{1cm} (5.3)

\[ V_{fc} = -\frac{1}{3} V_{f1} - \frac{1}{3} V_{f2} + \frac{2}{3} V_{f3} \]

Equation (5.3) can be rewritten in matrix form as:
Based on a switching function \( S_k \), the voltages \( V_{f1}, V_{f2}, \) and \( V_{f3} \) can be switched between three values; 0, + \( V_{DC} \), or -\( V_{DC} \). The switching function \( S_k \) of the \( k^{th} \) inverter leg \( (k = 1, 2, 3) \)

Can be defined as :

\[
S_k = \begin{cases} 
1, & \text{if } T_j \text{ is ON and } T_{j+3} \text{ is OFF} \\
0, & \text{if } T_j \text{ is OFF and } T_{j+3} \text{ is ON}
\end{cases} \quad j = 1, 3, 5 \quad (5.5)
\]

The voltages \( V_{f1}, V_{f2}, \) and \( V_{f3} \) can be written as

\[
\begin{pmatrix} V_{f1} \\ V_{f2} \\ V_{f3} \end{pmatrix} = \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix} \begin{bmatrix} 1/3 \\ 2 \\ -1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \begin{bmatrix} V_{DC} \end{bmatrix} \quad (5.6)
\]

Substitute (5.6) into (5.4) the SAPF phase-to-neutral voltages can be expressed as:

\[
\begin{pmatrix} V_{fa} \\ V_{fb} \\ V_{fc} \end{pmatrix} = \begin{bmatrix} 1/3 \\ 2 \\ -1 \end{bmatrix} \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \begin{bmatrix} V_{DC} \end{bmatrix} \quad (5.7)
\]

The switching vector \([S_1 S_2 S_3]\) can have eight possible switching states and based on these switching states the voltages \( V_{fa}, V_{fb}, \) and \( V_{fc} \) can be switched between five values as shown in table 5.1.
Table 5.1 Possible Switching State and the Corresponding Values of the Voltages $V_{fa}$, $V_{fb}$, and $V_{fc}$

<table>
<thead>
<tr>
<th>State #</th>
<th>$S_3$</th>
<th>$S_2$</th>
<th>$S_1$</th>
<th>$V_{fa}$</th>
<th>$V_{fb}$</th>
<th>$V_{fc}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2/3 $V_{DC}$</td>
<td>-1/3 $V_{DC}$</td>
<td>-1/3 $V_{DC}$</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>-1/3 $V_{DC}$</td>
<td>2/3 $V_{DC}$</td>
<td>-1/3 $V_{DC}$</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1/3 $V_{DC}$</td>
<td>1/3 $V_{DC}$</td>
<td>-2/3 $V_{DC}$</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>-1/3 $V_{DC}$</td>
<td>-1/3 $V_{DC}$</td>
<td>2/3 $V_{DC}$</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1/3 $V_{DC}$</td>
<td>-2/3 $V_{DC}$</td>
<td>1/3 $V_{DC}$</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>-2/3 $V_{DC}$</td>
<td>1/3 $V_{DC}$</td>
<td>1/3 $V_{DC}$</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

The variation in the voltages $V_{fa}$, $V_{fb}$, and $V_{fc}$ during the switching period make the derivation of the relation between the hysteresis band and the switching frequency difficult. For simplicity the average values of the voltages $V_{fa}$, $V_{fb}$, and $V_{fc}$ during one switching interval ($T_R$ or $T_F$) is adopted as in [13].

Figure 5.3 shows the average rising and falling current inside the hysteresis band in a conventional HCC, used to control the SAPF in Figure 5.2. The differential equations of the phase “a” current $I_a$ for the intervals $T_R$ and $T_F$ can be expressed as:
Figure 5.3 Average Rising and Falling Current

\[ L_f \frac{dI_{fa}^R}{dt} = Q_{fa}V_{DC} - V_a \]  \hspace{1cm} (5.8)

\[ L_f \frac{dI_{fa}^F}{dt} = -Q_{fa}V_{DC} - V_a \]  \hspace{1cm} (5.9)

\[ \frac{dI_{fa}^R}{dt} + \frac{dI_{fa}^F}{dt} = 0 \]  \hspace{1cm} (5.10)

where \( L_f \) is the coupling inductor of the SAPF, \( I_{fa}^R \) and \( I_{fa}^F \) are the respective average rising and falling current segments, \( Q_{fa}V_{DC} \) is the average applied voltage during either rising or falling segment (assumed to be the same), and \( V_a \) is the source voltage of the phase \( a \) measured at the connection point.
From the geometry of the Figure 5.3 the following equation can be deduced:

\[
\frac{dI^R_a}{dt} T_R - \frac{dI^F_a}{dt} T_R = 2HB \quad (5.11)
\]

\[
\frac{dI^F_a}{dt} T_F - \frac{dI^R_a}{dt} T_F = -2HB \quad (5.12)
\]

\[
T_R + T_F = T = \frac{1}{F_S} \quad (5.13)
\]

Add (5.11) and (5.12) and use (5.13):

\[
\frac{dI^R_a}{dt} T_R + \frac{dI^F_a}{dt} T_F - \frac{1}{F_S} \frac{dI^R_a}{dt} = 0 \quad (5.14)
\]

Subtract (5.12) from (5.11):

\[
\frac{dI^R_a}{dt} T_R - \frac{dI^F_a}{dt} T_F - (T_R - T_F) \frac{dI^F_a}{dt} = 4HB \quad (5.15)
\]

Substitute for \(\frac{dI^F_a}{dt}\) from (5.10) into (5.15):

\[
4HB = (T_R + T_F) \frac{dI^R_a}{dt} - (T_R - T_F) \frac{dI^R_a}{dt} = \frac{1}{F_S} \frac{dI^R_a}{dt} - (T_R - T_F) \frac{dI^R_a}{dt} \quad (5.16)
\]

Substitute for \(\frac{dI^F_a}{dt}\) from (5.10) into (5.14) and simplify:

\[
(T_R - T_F) = \frac{dI^F_a}{dt} / F_S \frac{dI^R_a}{dt} \quad \text{(5.17)}
\]

Substitute (5.17) into (5.16)
\[4HB = \frac{1}{F_S} \left[ \frac{dt R}{dt} - \left( \frac{dt^2 f_a}{dt^2} \right) \right] \]  

(5.18)

Substitute for \( \frac{dt R}{dt} \) from (5.8) into (5.18) and simplify:

\[F_S = \frac{Q f_a V_{DC} - V_a}{4H B L_f} \left[ 1 - \frac{m^2 L f^2}{(Q f_a V_{DC} - V_a)^2} \right] \]  

(5.19)

where \( m = \frac{dt^2 f_a}{dt} \) the slope of the reference current.

Equation (5.19) shows the viability of maintaining the switching frequency \( (F_s) \) constant if the hysteresis Band \( (HB) \) can be modulated to minimize the effect of the variation in the slope of the reference current \( (m) \), the phase voltage \( (V_a) \), and the supply voltage \( (Q f_a V_{DC}) \).

### 5.4 Proposed Algorithm

Figure 5.4 shows the block diagram for the proposed algorithm. The proposed algorithm inherits all the good merits of the conventional HCC algorithm because this algorithm is built around a conventional HCC algorithm with the modulation capability for the hysteresis band. It does not need any information about the system. Not as many other algorithms, used to tackle the variable switching frequency in Conventional HCC, it preserves the simplicity of the conventional HCC algorithm which makes it easy to be implemented. Also, this algorithm provides a direct measurement for the actual switching frequency, which enables a continuous assessment for the algorithm performance.
The proposed algorithm uses a closed-loop scheme that compares the output of asynchronous counter, driven by the actual switching pulses, to the output of synchronous counter, driven by a reference pulse signal with a user defined frequency.

![Proposed Adaptive HCC Algorithm Block Diagram](image)

Figure 5.4 Proposed Adaptive HCC Algorithm Block Diagram

Fig 5.5 shows the flow diagram of the proposed adaptive HCC algorithm. A conventional HCC, with a variable hysteresis band, is used to drive a three-phase SAPF. The error ($E$) between the output of reference synchronous counter and the
output of asynchronous counter, driven by the pulses of the conventional HCC, is calculated as:

\[ E = N_{\text{ref}} - N_{\text{act}} \quad (5.20) \]

where \( N_{\text{ref}} \) is the output of the reference synchronous counter and \( N_{\text{act}} \) is the output of the asynchronous counter.

While the error between these counters is zero, the controller will act as a conventional HCC. Once there is output error between the two counters, the controller will calculate a new value for the hysteresis band based on the sign and the value of that error as:

\[ H_{B_{\text{new}}} = H_{B_{\text{old}}} - \eta \times E \quad (5.21) \]

where \( H_{B_{\text{new}}} \) is the new calculated hysteresis band, \( H_{B_{\text{old}}} \) is the old hysteresis band, and \( \eta \) is a regulation factor.
Figure 5.5 Flow Diagram of the Adaptive RBFNN Algorithm
If the new calculated hysteresis band exceeds a preset values, for the upper ($ULim$) and lower ($LLim$) limits of the hysteresis band, the controller will take the limit value as the new value for the hysteresis band. Otherwise the controller will adopt this value as the new hysteresis band.

### 5.4.1 Example

To illustrate the proposed HCC algorithm; the following numerical example shows how the proposed algorithm updates the hysteresis band for a given scenario.

Assume the following scenario:

$$HB_{old} = 14 \text{ A}, \quad ULim = 25 \text{ A}, \quad LLim = 0.1 \text{ A}, \quad N_{ref} = 3, \quad N_{act} = 5, \quad I_{ref} = 300 \text{ A}, \quad I_{actual} = 315 \text{ A},$$

$\eta = 0.75 \text{ A}$, and the hysteresis band output is $I(ON)$.

According to the proposed algorithm, calculate the error $E$:

$$E = N_{ref} - N_{act} = 3 - 5 = -2$$

Which means the switching frequency is higher than the reference frequency and it needs to be adjusted.

Calculate the new hysteresis band $HB_{new}$:

$$HB_{new} = HB_{old} - \eta * E = 14 - 0.75 * -2 = 15.5 \text{ A}$$

The $HB_{new}$ is within the upper ($ULim$) and lower ($LLim$) limits. The calculated $HB_{new}$ will be adopted and the hysteresis band will be updated to be $15.5 \text{ A}$.

Now, calculate the current error ($\Delta I$):

$$\Delta I = I_{ref} - I_{actual} = 300 - 315 = -15 \text{ A}$$

To see the effect of the new algorithm, the following cases are considered:
With conventional HCC algorithm:

The $H_{B_{old}}$ cannot be updated and will remain equal to 14 A.

So with $\Delta I < H_{B} = -15 < -14$  
Output $= 0$ (OFF)

The hysteresis current controller will toggle its state and the output will be 0 (OFF) and the switching frequency will remain the same.

With proposed HCC algorithm:

The $H_{B_{old}}$ will be updated to the value 15.5 A.

So $\Delta I$ now is  
$-15 < H_{B} = -15.5 < -15 < 15$ , Output $= \text{remain the same } 1$ (ON)

The hysteresis current controller will keep its current state and the output will be 1 (ON), which increases the switching duration $T_{ON}$ and $T$ and reduces the switching frequency because $F_{S} = 1/T$.

5.5 Simulation Results

The proposed algorithm was used to control a SAPF system. The whole system was built in MATLAB/SIMULINK environment. The reference current was generated using the p-q theory [ref]. For simplicity the capacitor of the dc side of the SAPF is replaced by a constant voltage dc Battery. The SAPF system has the following parameters:
Voltage Source  400 V L-L, 60 Hz, source resistance 0.06 mΩ, source inductance 2 µH

Nonlinear Load  Three-phase thyristor rectifier with R-L load (450 kW active power, 200 kVAR reactive power)

Sampling Rate  5120 sample/ cycle

Ref. cycles #  3 cycles

Figure 5.6(a) shows the actual current of the SAPF and Figure 5.6(b) shows the reference current. The figure shows the ability of the proposed algorithm to track the reference current. Figure 5.7 shows the source current, it can be seen that the source current become almost sinusoidal the moments the SAPF is ON. The noise in this current can be easily filtered out by an external passive filter.
Figure 5.6 SAPF Output Current: Actual Current (a) Vs Reference Current (b)
To measure the performance of the proposed algorithm, its performance was compared with a conventional HCC for the same system parameters. The band width for the conventional HCC was set to (0.1) and the proposed algorithm was to move between a value of (0.1) as lower limit and a value of (30 A) as upper limit. Figure 5.8 shows the performance of both the conventional HCC and the proposed algorithm to maintain a 7 kHz reference switching frequency. The difference between the reference counter output and the counter driven by the generated pulses from the conventional HCC and the proposed algorithm is calculated and plotted against a reference line. The MSE for both algorithms was calculated. The proposed algorithm has a smaller (MSE= 9.93) compare to the conventional one (MSE= 303).
Figure 5.8 Performance of Both Proposed Algorithm (*) (MSE=9.93) and the Conventional (o) (MSE=303)

Figure 5.9 shows the resulting source current for both algorithms. Although both algorithms can achieve a sinusoidal source current, the conventional HCC in Figure 5.9(a) has fewer ripples, in the resulted current, than the proposed one in Figure 5.9(b). This can be explained by the narrow hysteresis band for the conventional HCC algorithm, which responses to small current error; while the allowable wide
hysteresis band for the proposed algorithm tolerates more current error in order to keep the switching frequency around the reference switching frequency.

Figure 5.9 Source Current for the Phase a Conventional HCC (a) and Adaptive RBFNN Algorithm (b)
The performance of the proposed algorithm was investigated under different values of reference switching frequencies, upper limit for the hysteresis band, and for regulation factor parameters. Figure 5.10 shows how the hysteresis band varies under different values of reference switching frequencies; Figure 5.10(a) for 10 kHz, Figure 5.10(b) for 15 kHz, and Figure 5.10(c) for 20 kHz. It can be seen from Figure 5.10 that for a given reference switching frequency, the magnitude of the hysteresis band varies within a window. The location of this window will move up and down depending on the value of the reference switching frequency. As the reference switching frequency goes up the window will move down. As seen in Figure 5.10(a) with a reference switching frequency equal to 10 kHz, the value of the hysteresis band is within the range of 19-25 A. On the other hand the hysteresis band is within the range of 5-15 A with 20 kHz reference switching frequency as seen in Figure 5.10(c). Also, the effect of the hysteresis band upper limit can be seen in Figure 5.10(a), where the value of the hysteresis band remain at the upper limit value (25 A) and cannot exceed that value. The consequence of the upper limit existence in the proposed algorithm is investigated in Figure 5.11. It can be seen that for a 7 kHz reference switching frequency, the MSE for performance of the proposed algorithm with upper limit is greater than the one without upper limit. But the importance of this limit is to permissible current error in this algorithm as illustrated for Figure 5.9. Figure 5.12 shows an example of the effect the upper limit value on the performance
of the proposed algorithm. It shows for a 10 kHz reference switching frequency, as the upper limit value goes up the MSE will be reduced.

Figure 5.10 Adaptive Hysteresis Band Variation for Different Reference Frequencies: (a) 10 kHz (b) 15 kHz (c) 20 kHz
Figure 5.13 shows the effect of the regulation factor on the performance of the proposed algorithm. Even though the MSE’s for the three tested values of the regulation factor (0.1, 0.5, and 1) were close, it can be seen that a reasonable higher regulation factor can help to prevent an excessive switching frequency and to enhance the fast response of the proposed algorithm.

![Figure 5.11 Performance of the Proposed Algorithm with and without Upper Limit for the Hysteresis Band](image)
Figure 5.12 Performance of the Proposed Algorithm for Different Values for the Upper Limits for the Hysteresis Band
Figure 5.13 Performance of the Proposed Algorithm for Different Regulation Factor Values: LR=0.1 MSE=4.99, LR=0.5 MSE= 5.23, and LR=1 MSE= 4.89
CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In this dissertation, the improvement of the SAPF performance was investigated by proposing different techniques for harmonic extraction and control of the SAPF. The RBFNN algorithm was used to extract and identify harmonics content in converter waveforms. The RBFNN training algorithm was based on the hybrid learning algorithm, which requires a short training time when compared to the conventional training methods. Two RBFNN networks were used to decompose the active power and the imaginary power into their DC and oscillating components. The algorithms were based on the p-q power theory, which gives flexibility in the choosing of a compensation strategy. The constant power and sinusoidal current compensation strategies were investigated. The results show good performance for decomposing the active and imaginary power. The algorithms performed very well in both transient and steady-state conditions. The simulations also showed that the methodology outlined here can be used to dynamically identify harmonics and for the elimination of harmonics using active power filters.

Also, the RBFNN algorithm was used to extract and estimate selective harmonics in converter waveforms. The results show that RBFNN can be used effectively for harmonic estimation in power signal. The investigation of the algorithm parameters
emphasizes the importance of these parameters on the performance of RBFNN. The simulation also showed that the methodology outlined here can be used to dynamically identify and estimate harmonics in relatively small size network. Even though this dissertation shows that the methodology has been applied for the identification of the first, fifth, and the seventh harmonics, the methodology can be extended to identify other harmonics not mentioned in this dissertation.

Also, in this dissertation, a novel adaptive RBFNN algorithm was proposed. This algorithm can overcome the disability of the conventional RBFNN systems to change their parameters after the end of the training phase. The performance of this algorithm to estimate the fundamental component and the total current of a converter wave was investigated. Nonlinear load, linear load, and white Gaussian noise signals were applied, to verify the performance of the proposed algorithm. The simulation results show the ability of the adaptive RBFNN algorithm to mitigate the effect of the noise signals on the performance of the system.

Finally, this dissertation proposed another novel adaptive hysteretic current controller. The proposed algorithm changes the hysteresis band in order to maintain nearly constant switching frequency. Also, this algorithm offers the user the capability of setting the reference switching frequency. The proposed algorithm was integrated with the p-q theory to represent a complete scheme for the control of the SAPF. The simulation results show the ability of the proposed algorithm to effectively track the reference signal, which obtained based on the p-q theory. The
results show that the proposed algorithm can nearly maintain a constant switching frequency under different reference switching frequencies. Also, the performance sensitivity of the proposed algorithm, to different values of its parameters (hysteresis band boundaries and regulation factor), was investigated. A comparison between the conventional HCC and the proposed algorithm was conducted for each of the above situations.

6.2 Future Work

The algorithms used or proposed in this dissertation need to be verified experimentally. Also the two novel algorithms proposed in this dissertation can be used in other fields. For example, the adaptive RBFNN algorithm can be used in the control applications, or the adaptive hysteresis current controller can be used in the motor drive applications.
BIBLIOGRAPHY


