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Total Harmonics Distortion Reduction Using Adaptive, Weiner, and Kalman Filters

Liqaa Alhafadhi
Western Michigan University

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TOTAL HARMONICS DISTORTION REDUCTION USING ADAPTIVE,
WEINER, AND KALMAN FILTERS

by

Liqaa Alhafadhi

A thesis submitted to the Graduate College
in partial fulfillment of the requirements
for the degree of Master of Science in Engineering (Electrical)
Electrical and Computer Engineering
Western Michigan University
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Thesis Committee:

Johnson Asumadu, Ph.D., Chair

Massood Atashbar, Ph.D.

Christopher Cho, Ph.D.

TOTAL HARMONICS DISTORTION REDUCTION USING ADAPTIVE, WEINER, AND KALMAN FILTERS

Liqaa Alhafadhi, M.S.E.

Western Michigan University, 2016

Total harmonics distortion is one of the main problems in power systems due to its effects in generating undesirable issues in power quality. These effects include heating (in transformers, capacitors, motors, and generators), disoperation of electronic equipment, incorrect readings on meters, disoperation of protective relays, and communication interference. Besides these problems, harmonics affect the power quality in both transmission and distribution systems. Different techniques have been used to mitigate the effects of harmonics. These techniques include; passive filters, active power filter, artificial intelligent, and adaptive selective harmonics reductions. Each method has some advantage and disadvantage.

This thesis presented new models of total harmonics distortion reduction using adaptive, Weiner, and Kalman filters. In order to test the performance of the presented methods, the output current of a single phase inverter circuit was used as a study case. The new models reduced the total harmonics distortion from by more than 50% however Kalman filters give the best performance as compared to adaptive and Weiner filters.

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Liqaa Alhafadhi

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CHAPTER 1

BACKGROUND AND MOTIVATION

1.1 Introduction

Harmonics have received great attention due to their effects in generating undesirable issues in power quality. These effects include heating (in transformers, capacitors, motors, and generators), disoperation of electronic equipment, incorrect readings on meters, disoperation of protective relays, and communication interference. Besides these problems, harmonics affect the power quality in both transmission and distribution systems. The effect of harmonics on power quality has received more attention from both utilities and customers. The main factors that make the power quality so important are; high level of harmonics in power system, the sensitive load equipment to power variation, the interconnection of any network that magnify the impact of failure, the awareness of customers about power quality issues. The main cause of harmonics is the nonlinear loads which affect the quality of the power in transmission and distribution systems.

Different techniques have been used to mitigate the effects of harmonics. Passive filters are the most common power filters that are used for harmonics reduction in power systems. These kind of filters are easy to installed and cost effective. However, large and different size of filters may be required for different harmonics orders, which may be cost effective [1]-[2]. Large number of filters may cause resonance, which leads to unstable system. If additional inductors or capacitors are used, the circuit becomes bulky. There is

a need for flexible and automated control but flexibility in control cannot be achieved using passive filters.

Active power filters (APF) techniques are commonly used to mitigate harmonics associated because APFs are more dynamic compared to the passive filters. The main principle of APF is to cancel harmonic components that are caused by nonlinear loads and to continuously and dynamically maintain low or eliminate harmonics to the load. In APF, the system parameters (current and voltage) are measured and compared to reference signals. Power Converters are used to realize the reference signals, which are injected into the load to eliminate the harmonics [3].

In addition to passive and active power filters, artificial neural networks (ANN) have been used also to reduce the harmonics effects and improve power quality. For example, ANN techniques that have been used include adaptive linear neuron (ADALINE), back propagation neural networks (BPNN), and radial basis neural networks (RBNN). Each one of these methods has some advantages and disadvantages as will be shown in Chapter 2 [4]-[5].

There are many more methods that have been developed but unfortunately the long term goal has not been satisfied yet. One of the methods that has become very common recently is the adaptive selective harmonics elimination (ASHE). The main concept of this technique is to attack one specific harmonic in selected frequency [6]-[7]. Most of the time the third harmonic is the targeted harmonic for elimination.

In this thesis, several new models based on adaptive, Kalman, and Winer filters will be considered for reducing undesirable harmonics in order to improve power quality. In

these models, all the harmonics contained in the distorted signal, not specific one as in other techniques which focused on one or two harmonics most of the time, will be considered. Different algorithms have been tested and all of them give an incredible results in terms of distortion reductions.

1.2 Thesis Goals

In this thesis, there are two main goals. The first one is to review some of the important techniques that have been used to improve the power quality by reducing the effect of harmonics. The second goal is to investigate different techniques of adaptive, Kalman, and Weiner filters as ways of improving the power quality. In the second goal the desire is to reduce and/or eliminate the effect of harmonics in all the frequencies contained in the distorted signal and find out which method gives the best performance in term of adaptation and speed, lowest total harmonics distortion (THD), and complexity.

1.3 Thesis Structure

The rest of the thesis are organized as follow; Chapter 2 covers in detail the currently used methods to overcome the harmonics problem in power and power electronics systems, Chapter 3 covers the proposed model, the results and discussion based on the models will be presented in Chapter 4, and finally in Chapter 5 the conclusions and future works will be presented.

CHAPTER 2

HARMONICS REDUCTIONS IN POWER AND POWER ELECTRONICS

In the past, harmonic distortion was not a big issue since the designs of power systems were very simple. Nowadays, harmonic distortion has increased with the use of complex designs in the industry. Much emphasis has been given to harmonic distortion associated with power quality. In an inverter input DC voltage is converted into AC output. During this conversion, harmonics affect the power quality. How harmonic reduction will help to improve the power quality will be explained in the following sections.

2.1 Harmonics

Harmonic is defined as a signal or wave with frequency that is an integer multiple of the fundamental frequency [8]. Besides the fundamental frequency f , an output signal may contain harmonics at frequencies of $2f$, $3f$, $4f$, and so on. The signal is a perfect sine wave if all energy is contained at the fundamental frequency. If some energy is contained within the harmonics, the signal is not a pure sinusoidal waveform, such as triangular wave, square wave, and saw tooth wave [8]. The non-sinusoidal waveform has odd and even harmonics. The odd harmonics are the most dangerous. The main reason behind harmonic distortion is nonlinear loads. A load is considered nonlinear if the current drawn by the load is non-sinusoidal even when it is connected to a sinusoidal voltage [3]. In order to protect the electrical devices from getting damaged due to harmonic voltage distortion, the harmonic current is isolated by using harmonic filters. These filters also help to improve the power quality. Much importance has been given to power quality because

the consumers are worried about power quality issues like interruption, sagging, and switching transients [9]. Also, a network has many power systems that are internally connected. If a failure exists in any one of the internal networks, whole system is affected due to the integration.

2.2 Harmonics Reduction Techniques

The number and variety of harmonics mitigation techniques now available does not make it easy or a straightforward process to select the best suitable method. Some of these techniques depend on the system condition in their performance, while the others require extensive system analysis. In this chapter these techniques will be classified into several categories.

2.2.1 Frequency Domain Techniques

In frequency domain techniques, the harmonic detection methods depend mainly on the Fourier transform method. These detection methods include three steps: 1) convert the distorted current or/and voltage from the time domain into frequency domain, 2) isolate the fundamental component from the harmonic in the frequency domain, and 3) reconstruct the compensating signal [3].

Girgis et al. [10] and Mariethoz [11] studied the use of the discrete Fourier transform (DFT) and the fast Fourier transform (FFT) for harmonic detection. To use either DFT or FFT, some conditions have to be satisfied. First of all, the signal to be processed must be periodic. Second, the samples window length must represent an integer number of a fundamental cycle. Third, the sampling frequency has to be equal to or greater than twice the highest harmonic frequency contained in the signal based on Nyquist criteria. Fourthly,

each harmonic included in the signal is an integer multiple of the fundamental frequency [10]-[11].

Komrska et al. [12] discussed the possibility of avoiding the high computation requirements for the classical DFT. In order to reduce the computational complexity, they estimated the fundamental harmonic instead of the whole spectrum of the signal. This technique is unsuitable for online application because the online applications are way more complex than the other ones.

Han [13] utilized the FFT algorithm to extract the harmonic components in the load current. The FFT algorithm is more efficient than DFT computationally because FFT requires $((N/2) \log_2 N)$ operations while DFT needs N^2 operations. The main problem of using FFT for online harmonic extraction is that it cannot be performed in each sampling period. Instead, an average of magnitude and phase is made to overcome the error due to the sampling. Also, compensation for phase delay is needed [13].

Borisov [14] and Maza- Ortega [15] used Recursive Discrete Fourier Transform (RDFT) which is a version of FFT suitable for online application. RDFT is more efficient than the DFT and FFT methods and it is also different from the two methods. RDFT is different by using a sliding window; usually this window is shifted one sample. For example, the spectrum of the window at time K is different from the spectrum of the window at time $K-1$ by the first and last sample. Therefore, there is no need to calculate the spectrum for the whole window [14]-[15]. This technique can be applied in real-time applications.

Habrouk [16] and Green et al. [17] addressed the disadvantages of using frequency detection methods which are the leakage problem, the synchronization between the

sampling frequency and the fundamental frequency, the large memory needed, the large number of computations, and the poor transient performance.

2.2.2 Time Domain Techniques

Time domain methods for harmonic detection can be applied in power system.

2.2.2.1 Filter Based Methods

Harmonics in nonlinear loads are considered a major problem in power system because they cause many issues such as overheating and temperature increase in generators. These effects may cause damages to the devices [18]. Filters are used to overcome the issues of harmonics. Filters are used widely for harmonic reduction with the increase of nonlinear loads in power system. Installing a filter helps in reducing harmonic for nonlinear loads connected in power system. There are two types of filters that are used in order to reduce the harmonic distortion. These are active filters and passive filters. Those filters are electronic devices that eliminate undesirable harmonics and distorted signals in the network. Active harmonic filters consist of active components such as IGBT-transistors, used only for low voltages. On the other hand, passive filters consist of passive components such as resistors, inductors, and capacitors used for different voltage levels [18]-[19]. Hybrid filter is also a third type of filter; a combination of both passive and active filters. Using filters would result in a better quality of power.

2.2.2.1.1 Passive Filters

As mentioned above, passive filters are used for different voltage levels. The passive filter is connected as either a parallel or a series resonant circuit with resistor, inductor, and capacitor. A parallel passive filter is a current acceptor while a series filter is

a voltage acceptor. Also, the filter provides maximum attenuation near the resonant frequency. The passive filter reduces or eliminates harmonic by attenuating the frequency of the harmonic. The reduced harmonic frequency must be equal to the resonant frequency of the circuit, thus the impedance of the network and the low impedance of the filter eliminate the harmonic current [18], [20]. Passive filters are used to reduce harmonic currents in the power system by minimizing the harmonics due to nonlinear loads. That is why the passive filters produce better results in reducing harmonics effect. Figure 2.1 shows a single phase representation of distribution system with nonlinear load and passive shunt filter.

A passive filter is only capable of eliminating one targeted harmonic [9]. For example, a passive filter design for eliminating 3rd harmonic will only eliminate this harmonic order. The resonance frequency of the passive filter must be lower than the frequency of the harmonic to be eliminated in order to avoid shift in frequency of the filter due to changes in the parameters of the filter [18].

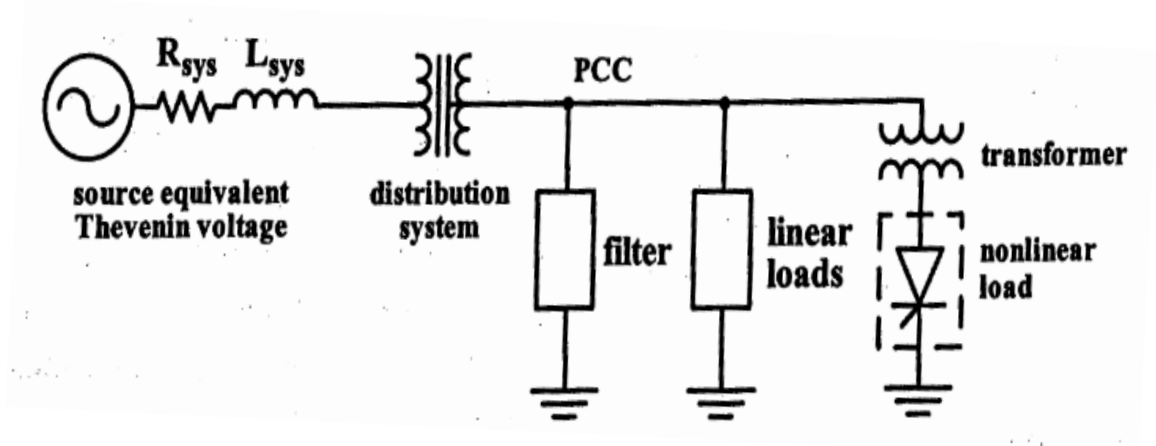


Figure 2.1: Single Phase Representation of Nonlinear Load and Passive Shunt Filter.

2.2.2.1.1.1 Types of Passive Filters

There are two types of passive filters

- Shunt passive filters
- Series passive filters

Both shunt and series passive filters are used for single phase and three phase power system. Also, more than one shunt and series passive filters can be used with and without each other in a system.

There are some differences between the shunt and series passive filters:

- a. The shunt passive filters carry only part of the total load current while the series passive filters carries the full load current [18].
- b. Compared to the series passive filters, shunt passive filter are cheaper so they are used more than the series ones [18].

Figures 2.2 and 2.3 show single phase passive filter with shunt and series configurations, respectively.

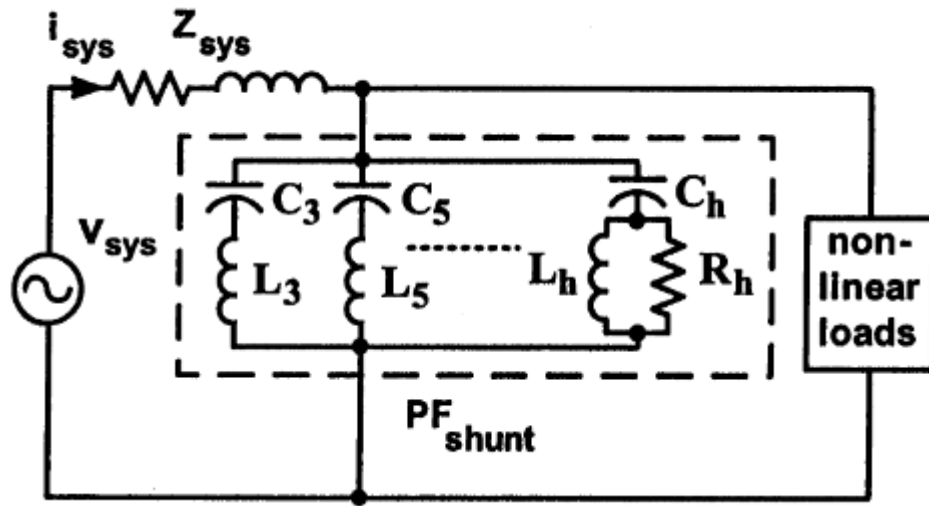


Figure 2.2: Single Phase Passive Filter with Shunt Configuration.

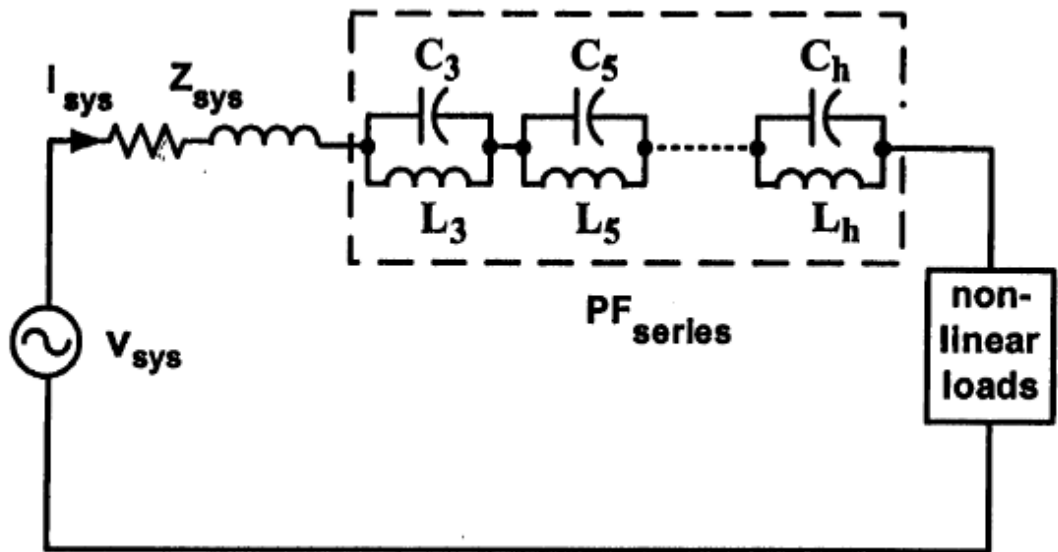


Figure 2.3: Single Phase Passive Filter with Series Configuration.

Figures 2.4 and 2.5 show three phase three wire passive filter for shunt and series configurations, respectively.

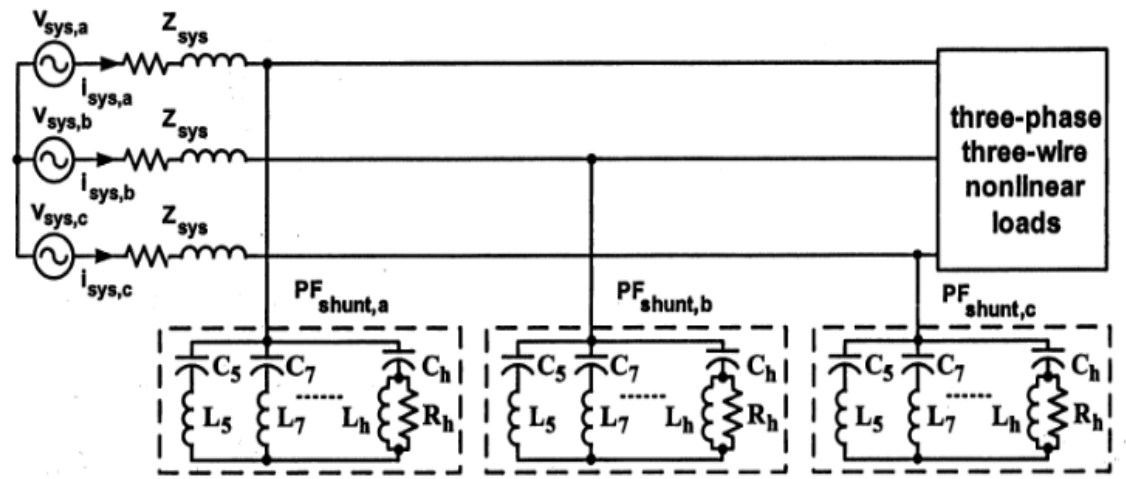


Figure 2.4: Three Phase, Three Wire Passive Filter for Shunt Configuration.

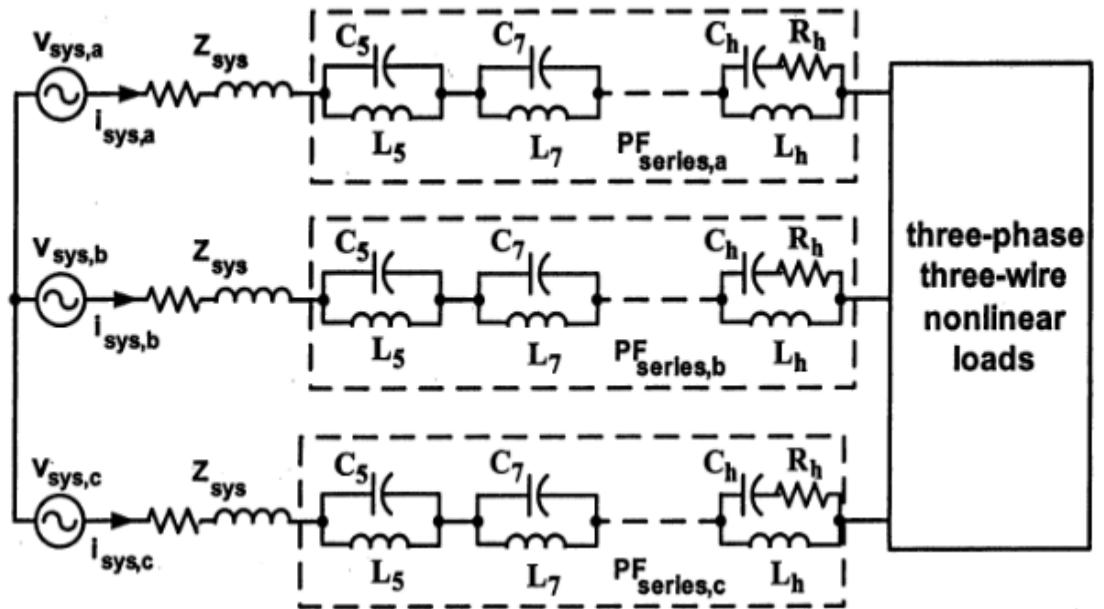


Figure 2.5: Three Phase, Three Wire Passive Filter for Series Configuration.

Three filters or more are usually connected in a system to reduce harmonics. To reduce the effect of harmonics which are less effective, the first two filters are connected and then a high pass filter is used. Figures 2.6 and 2.7 show shunt and series connected passive filters respectively.

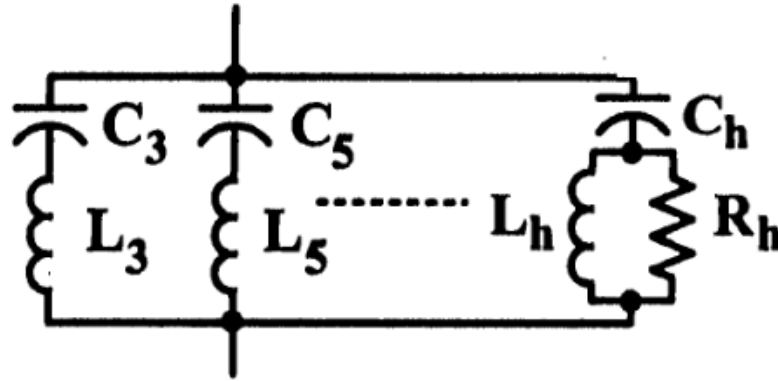


Figure 2.6: Shunt Passive Filter.

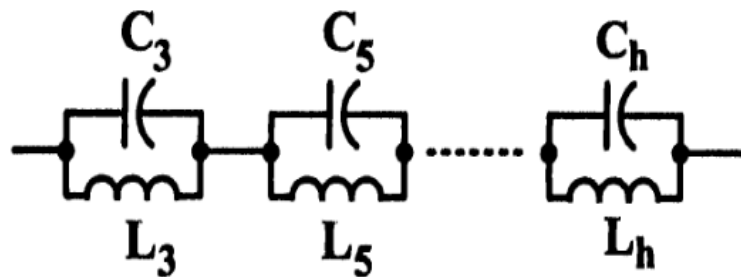


Figure 2.7: Series Passive Filter.

2.2.2.1.2 Active Filters

Where reactive power requirement is low, active filters are used for low voltages as explained earlier. These filters work as follow: the output load with the voltage

waveform is obtained by boosting the voltage throughout each half cycle by the filter. The power, which is produced tends to rectifiers in the power supply to gain current. The power factor and the duty cycle are thus improved. Also, the harmonics filters monitor the current that is produced due to load and generate a waveform which coincides with the exact shape of the nonlinear portion of the load current [18]-[20]. The output distortion is reduced, depending on the active harmonic filter used. Active filters are used in order to provide dynamic compensation where the harmonic orders change in terms of magnitudes and phase. They can be used in nonlinear load conditions where the harmonics dependent on the time. Depending on the source type which create harmonics in the power system, active filters can be connected in either series or parallel. Figure 2.8 and 2.9 show single phase active filters in shunt and series configuration respectively.

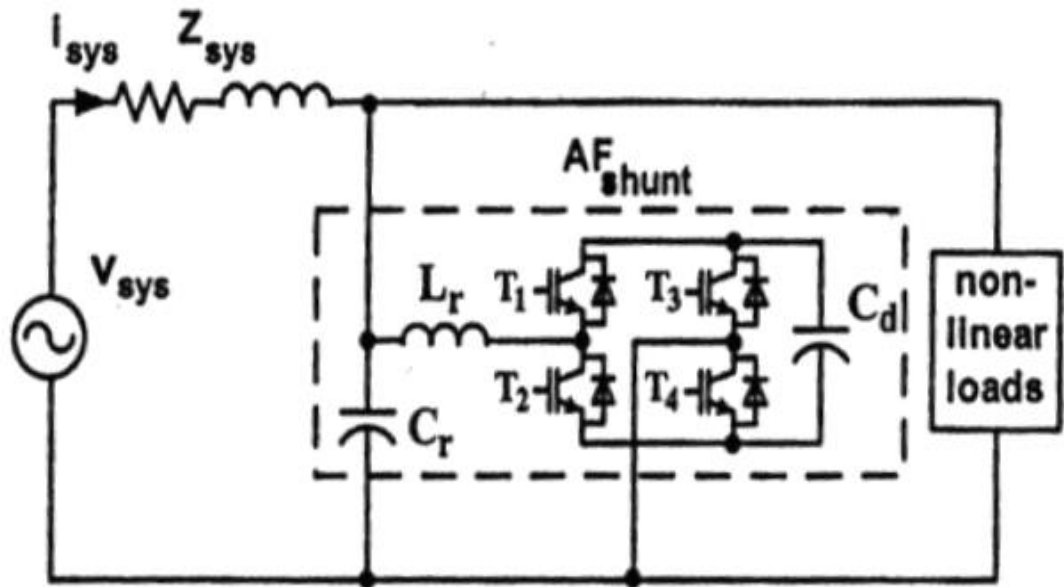


Figure 2.8: Single Phase Active Filter, Shunt Configuration.

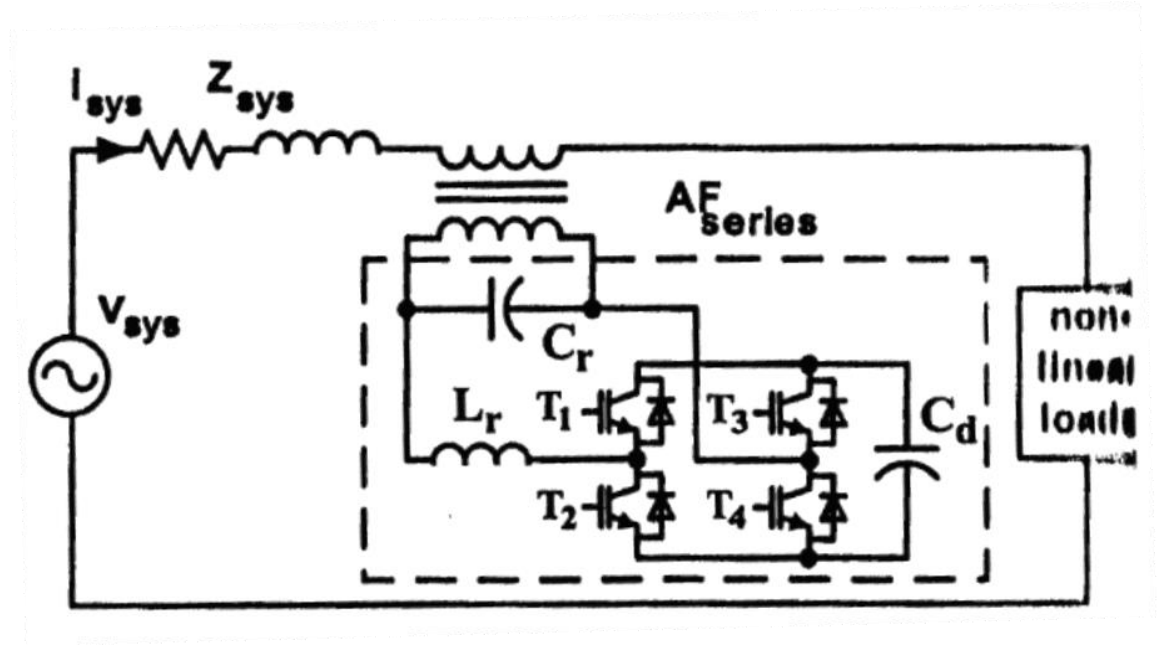


Figure 2.9: Single Phase Active Filter, Series Configuration.

The advantages of active filters includes the reduction of harmonics and useful for lowering flickering. But active filters are costly, cannot be used for small loads [18], and cannot be used in certain applications where harmonics are present in both the current and voltage.

More complex filters are needed in case where both current and voltage are leading to a direction in power system. These filters are made up of combination of active and passive filters which called as hybrid filters [18].

2.2.3 Artificial Intelligent Techniques

To overcome the disadvantages of time and frequency domain filters, the artificial intelligent filters have been used. There are three main techniques that have been used in artificial intelligent filtering (i) adaptive linear neuron (ADALINE), (ii) Feed Forward Multiplayer Perception (MLP), and (iii) radial basis function neural network (RBFNN).

2.2.3.1 Adaptive Linear Neuron

The most popular neural network technique used in active power filter is the ADALINE algorithm. The main reasons behind the popularity of this algorithm are the simplicity and the ease of hardware implantation. The ADALINE has the following features: (i) it has 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 method (LMS) to adjust its weights. Figure 2.5 shows the block diagram of the ADALINE algorithm [21].

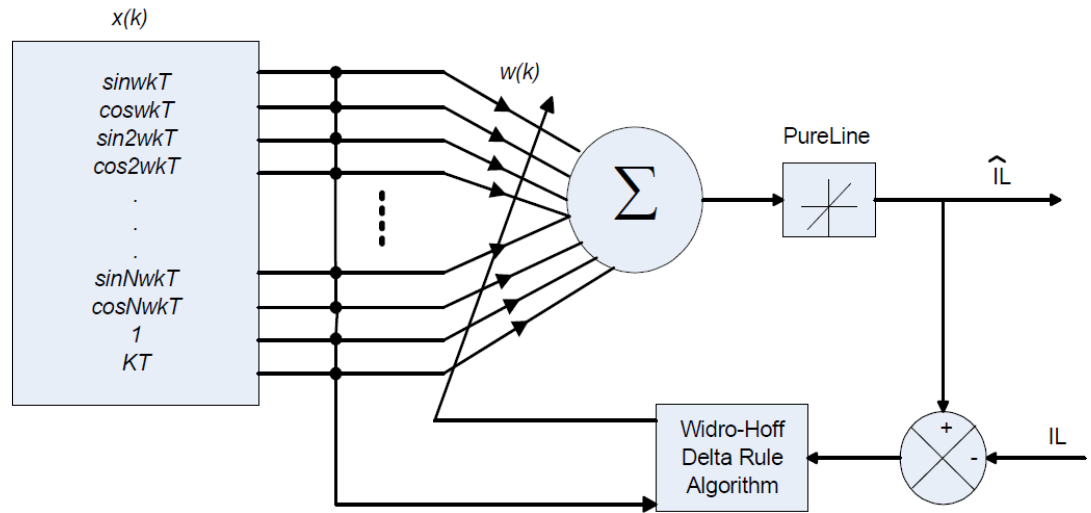


Figure 2.10: ADALINE Block Diagram by Zouidi.

The harmonics present in the polluted current represent the inputs of this network. The weights of this network represent the Fourier expansion coefficients. The weighted sum of the inputs multiply by a constant is the output. The error between the estimated load current and the actual load current is used to update the weights, based on Widrow-Hoff algorithm [21]. This was used by Zouidi et al to identify the discrete Fourier expansion

coefficients of harmonic polluted waveform. Based on these coefficients, the magnitude and the phase of the fundamental harmonic can be estimated.

2.2.3.2 Feed Forward Multilayer Perceptron (MLP)

To estimate the total harmonic contents for three phase nonlinear, Chen et al [22] used multi output MLP neural network with back propagation algorithm. Figure 2.6 illustrates the neural network structure used by Chen. According to Chen's proposed scheme, the firing angle in generating training data was constant. Some remarks can be noticed on Chen's proposed scheme: the architecture need to be tested for a wide range, the number of hidden neurons is large, and the training time is not mentioned.

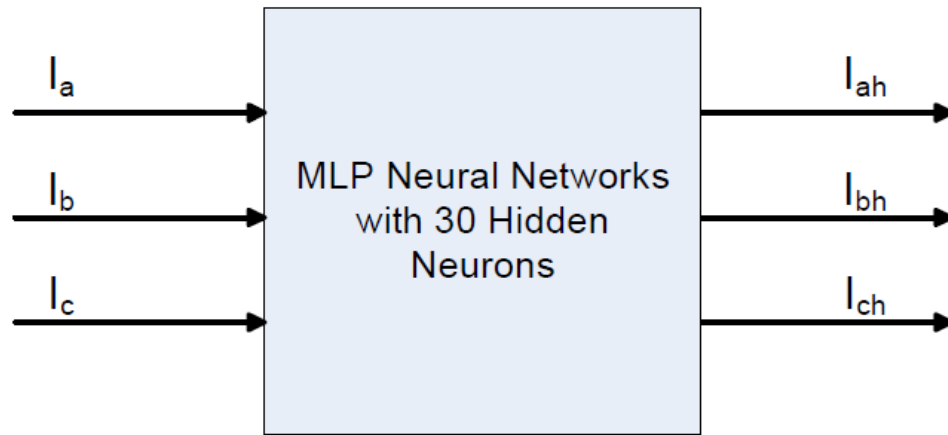


Figure 2.11: MLP Neural Network Architecture by Chen.

2.2.3.3 Radial Basis Neural Networks

Chang et al. [23] introduced radial basis function neural network (RBFNN) to extract selective harmonics. Figure 2.11 explains the neural network structure used by Chang. This algorithm uses similar training algorithm of back propagation. The input is a delayed vector of the polluted signal. The output is the value of the given harmonic order (first, third, fifth, or seventh). Just like the back propagation algorithm used in MLP, the error between the RBNN output and the desired input is used to update the weights and centers based on training algorithm [23].

2.2.4 Current Control Techniques

The choice of the control technique affects the performance of the active power filter. To resolve this issue, several current control techniques have been used for active power filter: such as space vector control, Proportional-Integral (PI) control, predictive control, deadbeat control, resonant control, sliding mode control, carrier phase shift, hysteresis current control, fuzzy control, and artificial neural network control [24]-[26].

Hysteresis current control technique is the most common one used in active power application because it shows distinct performance over the other control methods. The hysteresis current control has some advantages which are: simplicity, ease to implement, accuracy, fast response, and stability. However, it has the following disadvantages: variable switching frequency and interference in three phase case [24]. The main techniques used to improve the basic hysteresis techniques are:

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

- Neural network based hysteresis controller

More details about these techniques can be found in [27]-[30].

2.2.5 Adaptive Selective Harmonic Elimination Technique

Adaptive selective harmonic elimination (ASHE) algorithm has been used as a permanent solution in a wide range of power electronics applications. In power applications, control with objectives like fast response of system on reference and disturbance change is a primary objective. However, the algorithm of adaptive cancellation of selected harmonic components has been well developed in digital signal processing and filtering [6]-[7]. ASHE is used to eliminate undesirable higher harmonic components from selected variable current or voltage. This task requires only knowledge of the frequency of the components to be eliminated [31]. Figure 2.12 shows the structure of a single frequency adaptive selective harmonic elimination filter. The ASHE algorithm or filter, as shown in Figure 12.2, consists of combiner, least mean square (LMS) algorithm, and a summing point.

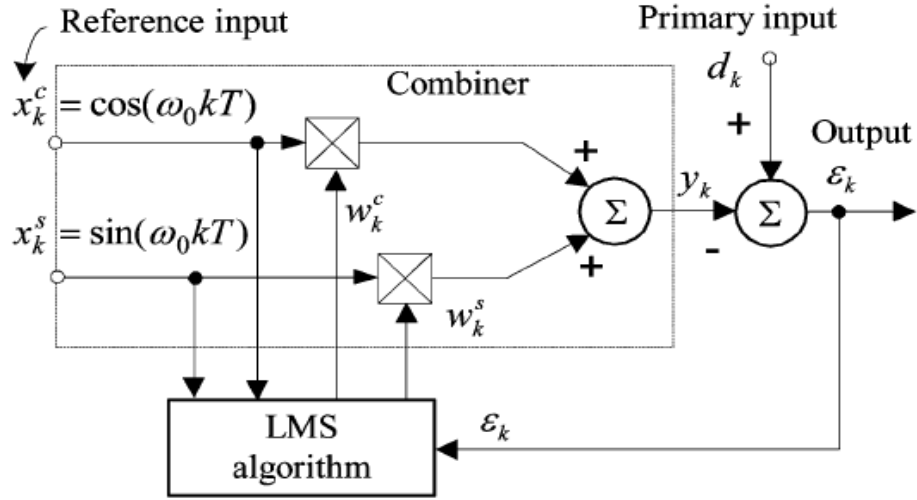


Figure 2.12: Structure of a Single Frequency Adaptive Selective Elimination technique.

The way this filter operates as following: the reference signal has two orthogonal components (cosine and sine) which is sampled at f_s . The frequency of the signal should be eliminated from the primary input signal. Multiply the reference input by the corresponding weights. Then, added the weighted sine and cosine components together to match the amplitude and phase angle of the primary input. The adaption process adjust the weights to match the amplitude and phase angle of the interfering sinusoid in the primary input [30]. The signal created by combiner is subtracted from the primary input to compute the error signal, which is also the output of the filter.

CHAPTER 3

ADAPTIVE FILTERING TECHNIQUES AND ALGORITHMS

This chapter presents the study case used in this thesis which is the inverter and what are the solutions to improve the quality of the inverters outputs.

3.1 DC-to-AC Converters (Inverters)

There is widespread use of power electronics inverters in filter applications. An inverter converts DC to AC with the desired amplitude and frequency [32]. The output AC voltage can be either single phase or three phase. Also, the magnitude of the AC voltage range varies and the frequencies are typically 50 HZ, 60 HZ, or 400 HZ.

The output current waveform of an ideal inverter is expected to be sinusoidal waveform, but in real applications they have distortions due to harmonics presence in the system which leads to distorted waveform [32]. The output signal will contain harmonics at frequencies of $2f_0$, $3f_0$, $4f_0$, and so on besides the fundamental frequency f_0 . The odd harmonics are the most dominant ones [33].

There are many applications of inverters; but the basic one would be an uninterruptible power supply (UPS). The other applications of an inverter is the variable frequency drives which controls the frequency and voltage of power supplied to the motor, thus controlling the speed of AC motor. Also, inverter is used to regulate the speed by changing the frequency of AC output [34]-[35]. There are three types of inverters:

- Single Phase Inverters

- Three Phase Inverters
- Multi-Level Inverters

3.1.1 Single-Phase Inverters

Single phase inverters have different topology. Figure 3.1 shows a single phase inverter. It is also called an H bridge inverter based on the way the switches and the load are connected. This single phase inverter consists of four choppers (for example, IGBT transistors with diodes in parallel). The loads are connected between the two IGBTs devices and the diodes. The way these diodes work is: when transistors S1 and S2 are on the transistors S3 and S4 will be off and the positive voltage appears on the load. Whereas when transistors S1 and S2 are off the transistors S3 and S4 will be on and the negative voltage appears on the load. In order to control the turning on and off of the IGBT circuits, different kinds of controllers can be used [32].

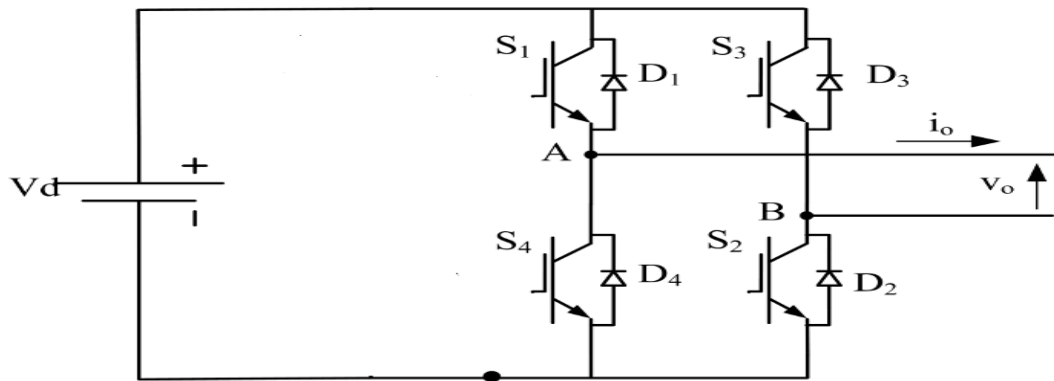


Figure 3.1: Single Phase Inverter.

3.1.2 Three-Phase Inverters

Three-phase inverters also have different topologies which can be used similar to the single phase inverter. Figure 3.2 shows a three phase inverter circuit. Three single phase inverters are connected to form the configuration of three phase inverter. There is a phase shift of 180 degrees between different legs in case of single phase inverter while in three phase inverter the phase shift is 120 degrees.

The 120-degree phase shift helps in eliminating the odd harmonics from the three legs of the inverter. Besides the odd harmonics, even harmonics can be eliminated as well if the output is pure AC wave form [35]. The way the three phase inverter works is almost similar to that of single phase inverter.

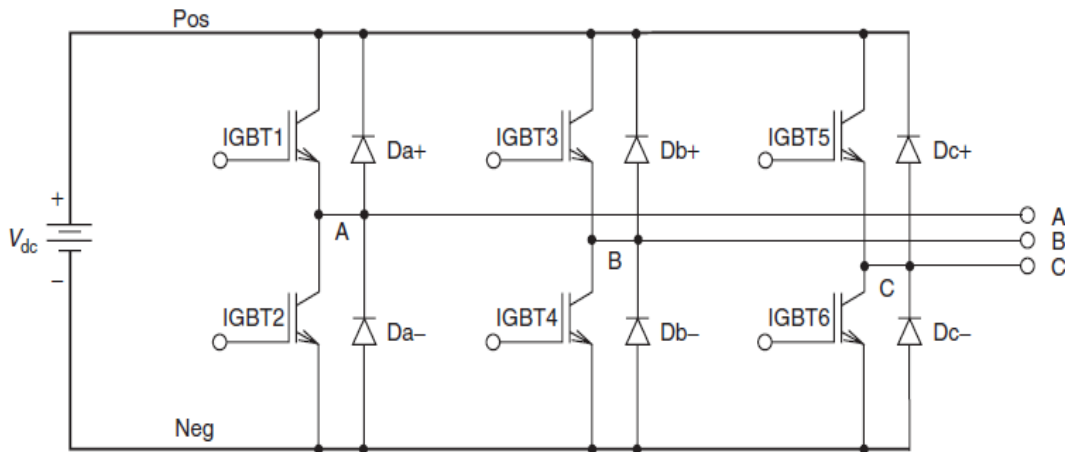


Figure 3.2: Three Phase Inverter.

3.1.3 Multi-Level Inverters

The construction of multi-level inverters is similar to the single and three phase inverters as explained earlier. Figure 3.3 shows a multi-level inverter circuit. It is an extension of single- and three-phase inverter circuits. As shown in the figure, four IGBT circuits are connected in three different legs and the diodes are connected in parallel to each legs in opposite direction. The loads are connected between two IGBT circuits for each leg.

The main advantages of using multi-level inverters instead of single- or three-phase inverters are as follow [9], [35]

- Multi-level inverters are used for high power applications.
- They have higher capability of reducing harmonics because of multiple DC levels.

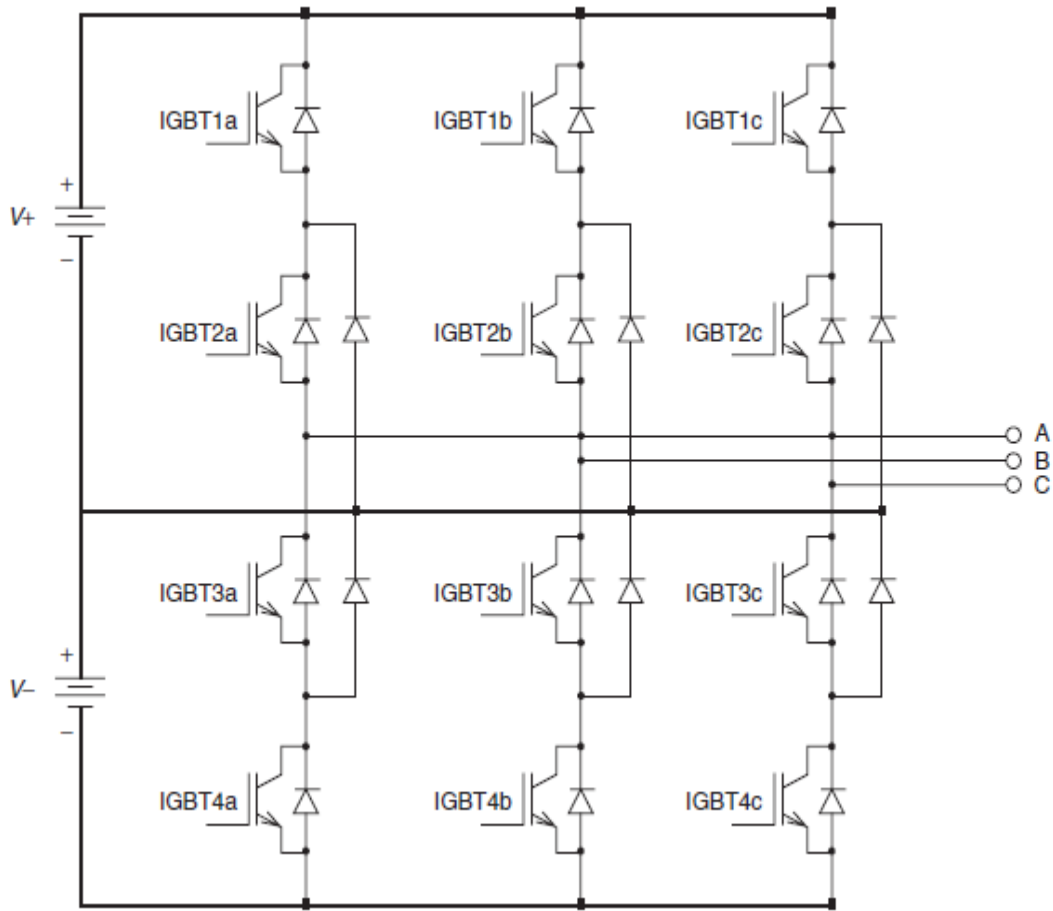


Figure 3.3: Multi Level inverter.

3.2 Adaptive Filtering Algorithms

It is very important to produce sinusoidal waveform since the output of DC to AC inverter is alternating. To do so, filters are implemented which reduce the harmonics effect by removing the third and higher order harmonics from the system. These filters consist of large number of inductors and capacitors which leads to more costly filters to remove the harmonics of higher order [34]-[35]. To avoid the cost of such expensive and complex filters, adaptive filter algorithms are applied. Adaptive filtering is a linear filter with ability

to change its weights iteratively in order to get the optimum solution of the cost function. Figure 3.4 describes the main concept of adaptive filter. The generated reference signal is the input to the adaptive filter and the output of the filter will be subtracted from the input signal to compute the error which is controlling the filter weights in order to reduce the error as much as possible. Based on the definition of the cost function and the known and unknown system parameters, there are many ways to reach the optimization goal. Sayed and Haykin mentioned different ways for approaching the optimization goals in their textbooks [36]-[37].

Adaptive filtering has been used widely for noise cancellation. Figure 3.4 illustrates the process in simple pictures. Least mean square (LMS) and normalized least mean square (NLMS) are the most popular algorithms that have been used successfully to reduce harmonics. Next sections will describe these algorithms in detail.

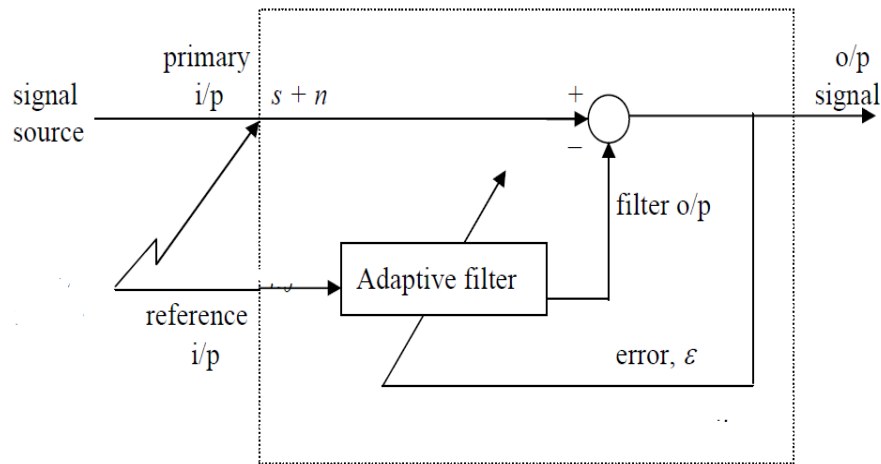


Figure 3.4: Adaptive filter as a noise canceller.

3.2.1 Least Mean Square Algorithm

LMS is the most common algorithm that has been used to reduce harmonics because of its distinguished properties. It has been used in different applications. It is simple, stable, and easy to implement. Its iterative process includes the following three steps: 1) compute the output of adaptive filter which, produce by a group of tap input, 2) generate an estimated error by comparing the output of the filter to a desired signal, and 3) use the error signal to adjust the tap weights [38]. Choosing the right value of step size is very important to control the stability and convergence speed of LMS algorithm. In this algorithm, the cost function is defined as the mean square error between the estimated output and the actual one. Using steepest descent in LMS algorithm to find the filter weights which minimize the cost function. The weights, error, and output equation of LMS algorithm can be derived as follow [36].

For a given adaptive filtering system with input matrix $\vec{x}(n)$, which is $M \times M$ matrix:

$$\vec{x}(n) = [x(n) \quad x(n-1) \quad \dots \quad x(n-M+1)] \quad (3.1)$$

where M is the filter taps and n is the number of current input samples. The output of the

adaptive filter will be $\vec{y}(n)$ which is:

$$\vec{y}(n) = [y(n) \quad y(n-1) \quad \dots \quad y(n-M+1)]^T = \vec{x}(n) \vec{w}(n)^T \quad (3.2)$$

where T refers to the transpose of the matrix and $\vec{w}(n)$ is the weight vector which is:

$$\vec{w}(n) = [w(0) \quad w(1) \quad w(2) \quad \dots \quad w(M-1)]^T \quad (3.3)$$

The main idea of LMS and other adaptive algorithms is to use steepest decent method to find the filter weight which minimize the cost function. The cost function $C(n)$ is defined as the expected value of the square of the error signal $\vec{e}(n)$. The error signal is the difference between the desired output $\vec{d}(n)$ and the actual one $\vec{y}(n)$:

$$\vec{e}(n) = [e(n) \quad e(n-1) \quad \dots \quad e(n-M+1)]^T \quad (3.4)$$

$$\vec{d}(n) = [d(n) \quad d(n-1) \quad \dots \quad d(n-M+1)]^T \quad (3.5)$$

Based on the definition of the cost function,

$$C(n) = E \left[\left| \vec{e}(n) \right|^2 \right] \quad (3.6)$$

where $e(n)$ is the error at the current sample n and E is the expected value. If we apply the steepest decent method then this means taking the partial derivatives with respect to the individual filter weights:

$$\nabla_w C(n) = \nabla_w E \left[\left| \vec{e}(n) \right|^2 \right] = 2 \vec{e}(n) \frac{\partial \vec{e}(n)}{\partial w} \quad (3.7)$$

But

$$\vec{e}(n) = \vec{d}(n) - \vec{x}(n) \vec{w}(n)^T \quad (3.8)$$

Hence

$$\frac{\partial \vec{e}(n)}{\partial w} = -\vec{x}(n) \quad (3.9)$$

To take the minimum of the cost function, take a step in the opposite direction of $\nabla_w C(n)$. To express this point mathematically:

$$\vec{w}(n+1) = \vec{w}(n) - \frac{\mu}{2} \nabla_w C(n) \quad (3.10)$$

$$\vec{w}(n+1) = \vec{w}(n) - \frac{\mu}{2} \cdot 2 \cdot \vec{e}(n) \cdot -\vec{x}(n)$$

$$\vec{w}(n+1) = \vec{w}(n) + \mu \cdot \vec{x}(n) \cdot \vec{e}(n) \quad (3.11)$$

where μ is the step size. Equation (3.11) is the weight update which is the relationship between the current weight vector and the next step.

3.2.2 Normalized Least Mean Square Algorithm

The filter length and the power of the signal affect on the stability, convergence, and steady state behavior of the LMS algorithm. To solve this problem, NLMS which is a variant of the LMS has been used widely. It solves the problem by normalizing the power of the input. In the NLMS algorithm, all the equations mentioned in the previous section stay the same except the weight update equation will change as follow [36]:

$$\vec{w}(n+1) = \vec{w}(n) + \frac{\mu}{\varepsilon + \|\vec{x}(n)\|^2} * \vec{x}(n)^H * \vec{e}(n) \quad (3.12)$$

where $\|\vec{x}(n)\|^2 = \vec{x}(n)^H * \vec{x}(n)$ is the normalizing factor, H denotes the complex conjugate transposed, and ε is the regularization size.

3.2.3 Leaky Least Mean Square Algorithm

It is very hard to approach the stability of LMS algorithm without choosing a learning rate of the step size that guarantee the stability. To deal with this problem a variant of LMS used, which is leaky LMS algorithm. This algorithm also designed to overcome the slow convergence of LMS [39]. In leaky LMS, the input, the output, and the error signals stay the same as in LMS. The change will happen in the weight update equation as follow:

$$\vec{w}(n+1) = (1 - \mu * \eta) \vec{w}(n) + \mu * e(n) * \vec{x}(n) \quad (3.13)$$

where η is the leaky factor, which is a very small positive number ($\eta \ll 1$).

3.2.4 Sign LMS and Sign NLMS Algorithms

These two algorithms are exactly similar to LMS and NLMS. The only difference is the weight update equations. In LMS and NLMS, the equations depends on the error signal. Whereas in sign LMS and sign NLMS use the sign of the error signal only to update the weight equations as shown in (3.14) and (3.15) respectively:

$$\vec{w}(n+1) = \vec{w}(n) + \mu * \text{sgn}(e(n)) * \vec{x}(n) \quad (3.14)$$

$$\vec{w}(n+1) = \vec{w}(n) + \frac{\mu}{\varepsilon + \|\vec{x}(n)\|^2} * \text{sgn}(e(n)) * \vec{x}(n) \quad (3.15)$$

where $\text{sgn}(e(n))$ refers to the sign of the signal $e(n)$.

3.3 Wiener Filter

Wiener filter is a class of linear optimum discrete time filters. The main goal of using these filters is to minimize an appropriate function of error which is known as the cost function [38]. The most commonly cost function that used in optimum filters is the mean square error (MSE). Minimizing the MSE includes the second order statistics only and leads to a theory of linear filter that is useful in many applications. The Wiener filters can be used in different applications such as image processing, signal processing, control system, and digital communication. Figure 3.5 explains the main concept of Wiener filter.

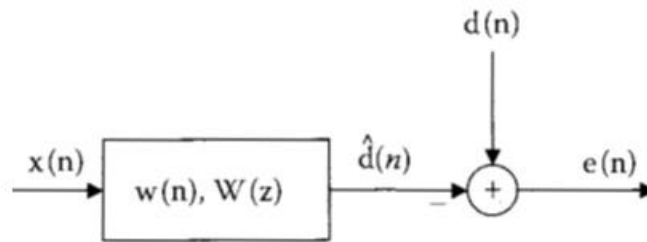


Figure 3.5: Block Diagram of Wiener Filter.

The basic idea is that Wiener filter was designed to produce an estimate signal $\hat{d}(n)$ of the desired signal $d(n)$ using a linear combination of the data $x(n)$ such that the mean square error function is minimized. This process includes filtering, smoothing, predication, and deconvolution.

Assuming the processes $x(n)$, $d(n)$, etc., have zero mean value and the filter coefficients do not change with time. The output is equal to the convolution of the input and the filter coefficient. Hence [38]

$$\hat{d}(n) = \sum_{m=0}^{M-1} w_m x(n-m) = \mathbf{w}^T \mathbf{x}(n) \quad (3.16)$$

where M is the number of filter coefficients, \mathbf{w}^T is the filter weights as in adaptive filter, and

$$\mathbf{x}(n) = [x(n), x(n-1), \dots, x(n-M+1)]^T$$

The cost function J is defined as the minimum mean square of the difference between the actual output and desired one.

$$J = E\{(d(n) - \hat{d}(n))^2\} = E\{e^2(n)\} \quad (3.17)$$

With some simplification:

$$\begin{aligned} J(\mathbf{w}) &= E\{e^2(n)\} = E\{[d(n) - \mathbf{w}^T \mathbf{x}(n)]^2\} \\ &= E\{[d(n) - \mathbf{w}^T \mathbf{x}(n)][d(n) - \mathbf{w}^T \mathbf{x}(n)]^T\} \\ &= E\{d^2(n) - \mathbf{w}^T \mathbf{x}(n)d(n) - d(n)\mathbf{x}^T(n)\mathbf{w} + \mathbf{w}^T \mathbf{x}(n)\mathbf{x}^T(n)\mathbf{w}\} \\ &= E\{d^2(n) - 2\mathbf{w}^T E\{d(n)\mathbf{x}(n)\} + \mathbf{w}^T E\{\mathbf{x}(n)\mathbf{x}^T(n)\}\mathbf{w}\} \\ &= \sigma_d^2 - 2\mathbf{w}^T \mathbf{P}_{dx} + \mathbf{w}^T \mathbf{R}_x \mathbf{w} \end{aligned}$$

where σ_d^2 is the variance of the desired signal $d(n)$, and \mathbf{P}_{dx} is the cross correlation vector between $d(n)$ and $\mathbf{x}(n)$.

$$\mathbf{P}_{dx} = [\mathbf{P}_{dx}(0), \mathbf{P}_{dx}(1), \dots, \mathbf{P}_{dx}(M-1)]^T \quad (3.18)$$

$$\begin{aligned}
P_{dx}(0) &= r_{dx}(0), P_{dx}(1) = r_{dx}(1), \dots, P_{dx}(M-1) = r_{dx}(M-1) \\
R_x &= E \left\{ \begin{bmatrix} x(n) \\ x(n-1) \\ \vdots \\ x(n-M+1) \end{bmatrix} \begin{bmatrix} x(n), x(n-1), \dots, x(n-M+1) \end{bmatrix} \right\} \\
&= \begin{bmatrix} E\{x(n)x(n)\} & E\{x(n)x(n-1)\} & \dots E\{x(n)x(n-M+1)\} \\ E\{x(n-1)x(n)\} & E\{x(n-1)x(n-1)\} & \dots E\{x(n-1)x(n-M+1)\} \\ E\{x(n-M+1)x(n)\} & E\{x(n-M+1)x(n-1)\} & \dots E\{x(n-M+1)x(n-M+1)\} \end{bmatrix} \\
&= \begin{bmatrix} r_x(0) & r_x(1) & \dots r_x(M-1) \\ r_x(-1) & r_x(0) & \dots r_x(M-2) \\ r_x(-M+1) & r_x(-M+2) & \dots r_x(0) \end{bmatrix}
\end{aligned} \tag{3.19}$$

The R_x matrix is the correlation matrix of the input data, and it is symmetric because the random process is assumed to be stationary. Updating the filter weights in Weiner filter is not that easy as in adaptive filter, even if they follow the same path. A detailed process on how to update these weights are available in [37]-[38].

3.4 Kalman Filter

Kalman filter has become very popular in different applications such as tracking objects, in economics, navigation, computer vision, and many more. It has widely used to control noisy system. The main idea of Kalman filter is to reduce the noise by extracting the useful data from the noisy one. For this approach, it uses immediate measured power [40]. In addition to noise reduction, Kalman filter can be used to estimate the states of the system. Power engineers used this filter to estimate failure probability which is considered

very helpful [41]. By using Kalman filter, it is possible to achieve good results. This section will present some of Kalman filter's applications.

Kalman filter has been widely applied to the Global Positioning System (GPS) which is satellite based navigation system that provides users with the proper equipment to useful and accurate positioning information anywhere on the globe. The only problem could be due to the modeling error using Kalman filter in navigation process is divergence. To overcome this problem Jow, et al [42] proposed three strategies. First, applying adaptive filter algorithms to prevent divergence of extended Kalman filter (EKF) in case the precise knowledge on the system are not available. Second, deriving a better nonlinear dynamic process model and then utilizing an appropriate nonlinear estimate approach. Finally, interacting multiple model (IMM) algorithms takes into account for different maneuvering conditions. IMM has been used to allow the possibility of using high dynamic model in the problem of divergence and then improve the estimation accuracy.

Kalman filter was also used successfully as a motion estimator in video coding [43]. It is considered to be one of the most common tools that is extremely used in signal processing field especially speech enhancement and speaker tracking [44].

Dikonomou et al [45] focused on the application of Kalman filter in the Electroencephalogram (EEG) processing. They presented the difference between the Kalman filter (KF) and the Kalman smoother (KS) based on how they use the observations to perform estimation.

In the last few years Kalman filter techniques have been used successfully for noise cancellation to approach high precision and fast convergence. The work of Kazimi et al

[46] focused on two areas which are audio noise cancellation and electrocardiogram (ECG) noise filtering.

Based on the previous significant applications of Kalman filter, a new model of harmonic reduction using Kalman filter is introduced. In addition to all applications of Kalman filter mentioned earlier, this filter was used perfectly to reduce harmonics. It was applied to attack all harmonics contained in the distorted signal and good results were obtained. The technique of Kalman filter works very well to get rid of harmonics that exist in the output current signal. The strategy is similar to noise cancellation using Kalman filter. The simplicity of derived equations and the other properties make it easy to use Kalman filter for harmonic reduction.

In linear dynamic system, Kalman filters are discretized in the time domain. The state of the system is represented as a vector of real numbers. Figure 3.6 shows a block diagram of a discrete time system with processed and some noise mixed in it. Kalman filter was used in order to estimate the internal state of the process given only a sequences of noisy observations. The process must be modelled in accordance with the framework of Kalman filter as follow:

$$\mathbf{x}_j = \mathbf{A} \mathbf{x}_{j-1} + \mathbf{B} \mathbf{u}_j + \mathbf{w}_j \quad (3.20)$$

$$\mathbf{z}_j = \mathbf{H} \mathbf{x}_j + \mathbf{v}_j \quad (3.21)$$

where \mathbf{A} is the state matrix gain, \mathbf{B} is the input matrix gain, \mathbf{w}_j is the process noise, \mathbf{H} is the output matrix gain, \mathbf{v}_j is the measurement noise, and j is the time variable.

At each step the initial state and the noise vectors are assumed to be mutually independent $\{x_0, w_1, \dots, w_j, v_1, \dots, v_j\}$. Figure 3.6 is a corresponding block diagram of the system described in (3.20) and (3.21).

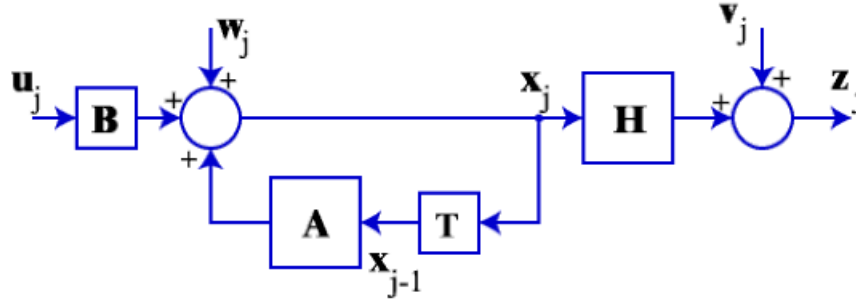


Figure 3.6: A Discrete Time system with Process w and Measurement Noise v .

Since Kalman filter is a recursive estimator, the estimated states from previous time step and current measurement are needed to estimate for the current state. The state of the filter is represented by two variables X , and P . The block diagram of Kalman filter is shown in Figure 3.7. Kalman filter is most often written as two distinct phases: “predict” and “update”. The predict phase uses the state estimate from previous time step to produce an estimate of the state at the current time step, which is also known as the a priori state estimate. In the update phase, the current a priori prediction is combined with current observation information to refine the state estimate. This update state estimate is also known as the *posteriori state estimate*. The predictor equation is given by

$$\hat{x}_j = A\hat{x}_{j-1} + Bu_j \quad (3.22)$$

where $\hat{\mathbf{x}}_j$ and $\hat{\mathbf{x}}_{j-1}$ are the current and the previous estimated states respectively.

The update equation is given by

$$\hat{\mathbf{x}}_j = \hat{\mathbf{x}}_j^- + \mathbf{K}_j (\mathbf{z}_j - \mathbf{H} \hat{\mathbf{x}}_j^-) \quad (3.23)$$

where \mathbf{K}_j is the Kalman gain. The priori \mathbf{P}_j and a posteriori \mathbf{P}_j covariance matrix are given by:

$$\mathbf{P}_j = E\{\mathbf{e}_j \mathbf{e}_j^T\} = \{(\mathbf{x}_j - \hat{\mathbf{x}}_j)(\mathbf{x}_j - \hat{\mathbf{x}}_j)^T\} \quad (3.24)$$

$$\mathbf{P}_j = E\{\mathbf{e}_j \mathbf{e}_j^T\} = \{(\mathbf{x}_j - \hat{\mathbf{x}}_j)(\mathbf{x}_j - \hat{\mathbf{x}}_j)^T\} \quad (2.25)$$

where E is the expected value, \mathbf{e}_j is the difference between the estimated and the true value of the state, and T is the matrix transpose.

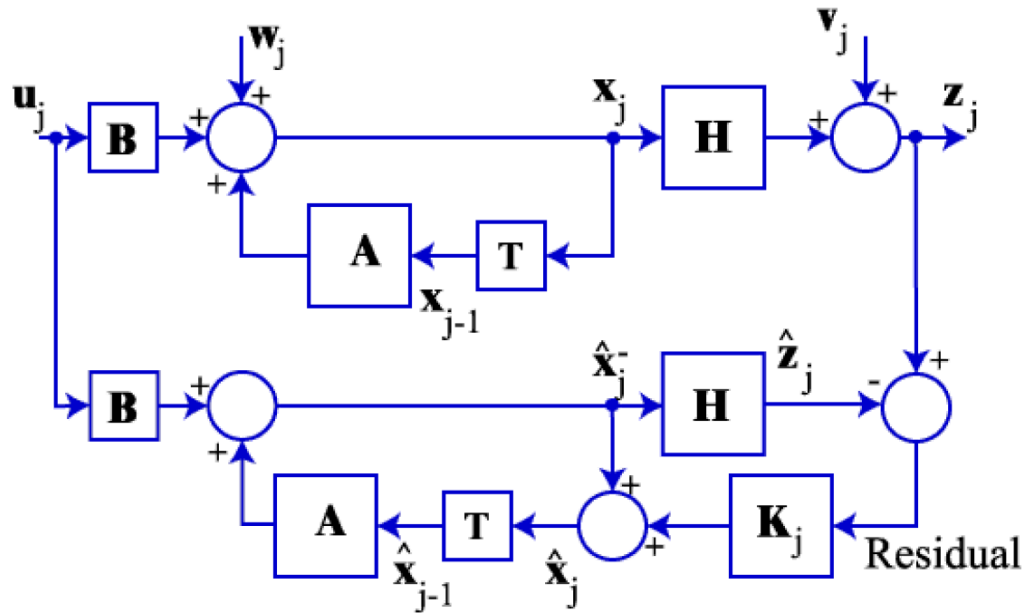


Figure 3.7: Block Diagram of Kalman Filter.

CHAPTER 4

SIMULATION AND RESULTS

This chapter presents the simulations and results of the study case described in this thesis and what are the suggested solutions and how they perform.

4.1 DC-AC Converter in MATLAB SIMULINK

A single-phase inverter, shown in Figure 4.1, was simulated in MATLAB/SIMULINK [47] to study its performance in terms of power quality. The simulated circuit is shown in Figure 4.2. As shown in the figure, there are four choppers (transistors with diodes in parallel). When transistors S1 and S2 are turned on and S3 and S4 are off, positive voltage appears at the load. When transistors S3 and S4 are turned on and S1 and S2 are off, negative voltage appears at the load [32]. The amplitude of the output voltage is equal to the value of the DC voltage source. The simulation parameters of the inverter circuit were selected as follow: $V_{dc} = 600$ V, the load was RL load with $R = 0.5$ Ohm and $L = 1.592$ mille Henry. PWM is a common method for controlling the switches of the inverters [32]. For the simulation of single phase switches controller, we use PWM generator block in MATLAB/SIMULINK with the following parameters: two arms generator mode, 1000 Hz carrier frequency, 0.6 modulation index, 60 Hz frequency of the output voltage, and 0 degree phase shift of the output voltage. The output current and voltage of this inverter will be distorted, as shown in Figure 4.3.

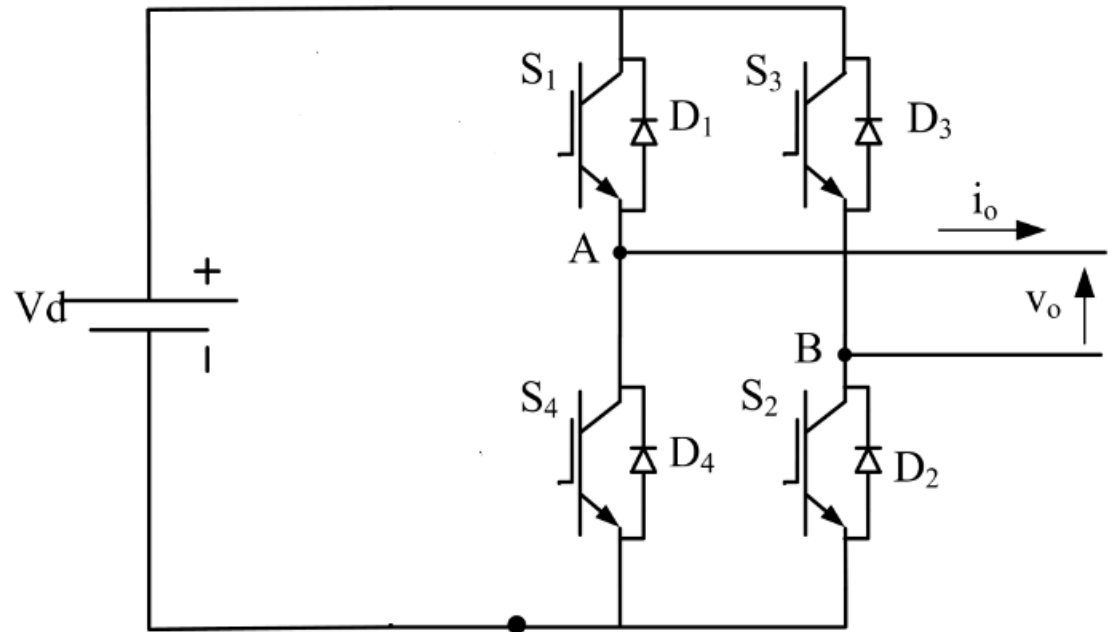


Figure 4.1: Single Phase Inverter.

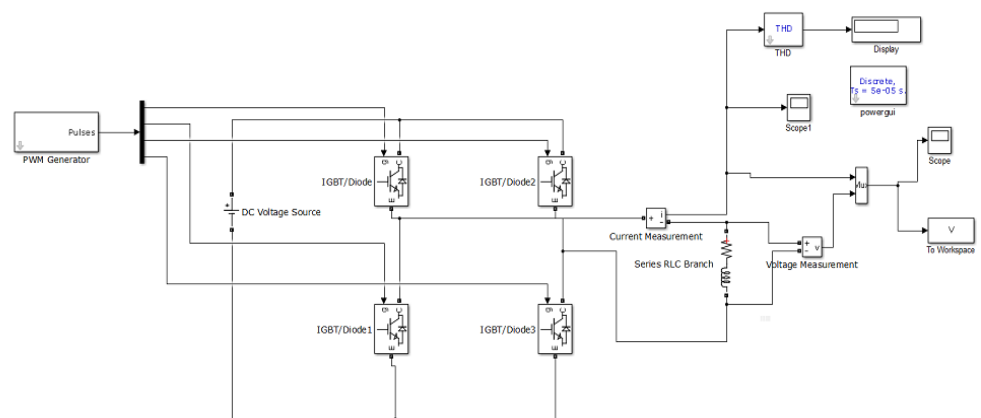


Figure 4.2: Simulated Inverter in MATLAB.

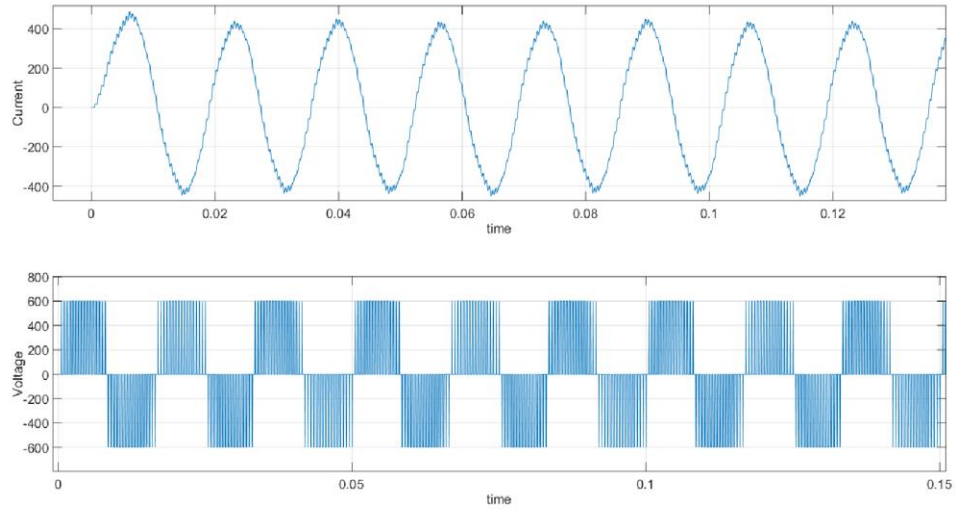


Figure 4.3: Inverter's Output Current and Voltage for RL Load.

The main cause of the distortion is the harmonics. To study the possible techniques that we suggested in chapter III for harmonics reduction, we chose to focus on the current signal only.

4.2 Distortion Reduction Using New Adaptive Filtering Models

The distorted current signal of single phase inverter was used in this thesis. LMS, NLMS, Leaky LMS, sign LMS, and sign NLMS algorithms are used as adaptive filtering techniques to clean the signal. Instead of generating reference signal as in Figure 4.4, a delayed version of the signal was used as input signal for the adaptive filter as shown in Figure 4.5. The output signal of the adaptive filter was subtracted from the distorted input signal to obtain the error signal, which is responsible for controlling the weights of the adaptive filter. The error and filter weights are computed in each iteration based on the

equations described in Chapter 3 for each algorithm. Instead of focusing on specific harmonics as in ASHE, all harmonics contained in the distorted signal are targeted for elimination. For certain values of step size (μ) and filter length (M), Adaptive filtering algorithms gave a very clean signal compared to the distorted one as shown in Figures 4.6-4.10. These algorithms are very powerful in reducing the distortion despite the time required for the adaptation process. During this time the output current seems to be different from the rated values but there is no overshoot in the signal. In LMS algorithm, the step size has to be very small (example $1e-8$ range) to reach the adaption goal while in NLMS the goal is reached with higher values of step size (example 0.01). Based on Figures 4.6-4.10, we can say that NLMS and sign NLMS are better than other algorithms in term of step size. If we ignored this term, then all algorithms give a good performance. The MATLAB code for LMS algorithm is shown in Figure. 4.11. For NLMS, sign LMS, sign NLMS, and Leaky LMS, the weight equations are updated and the LMS code is modified, as shown in Figures 4.11-4.13. Signed LMS and signed NLMS use the same code as in LMS and NLMS, respectively. The only change is to use the function $\text{sgn}(e(n))$ in the weight update equations. The total harmonic distortion (THD) of the distorted current signal before processing was 4.9%. With adaptive filters, the THD is reduced to 2.5 - 3%. Leaky LMS gives the best performance in term of THD reduction. The THD reduction using adaptive filters seem to be less effective even if the output signal looks very clean after the processing. The main cause is the short time that adaptive filters need to reach their optimization goal, which explains why the output signal is not stable in the beginning. If the load was changed in a certain way so the THD got increase adaptive filters are still be able to reduce it by more than 50%.

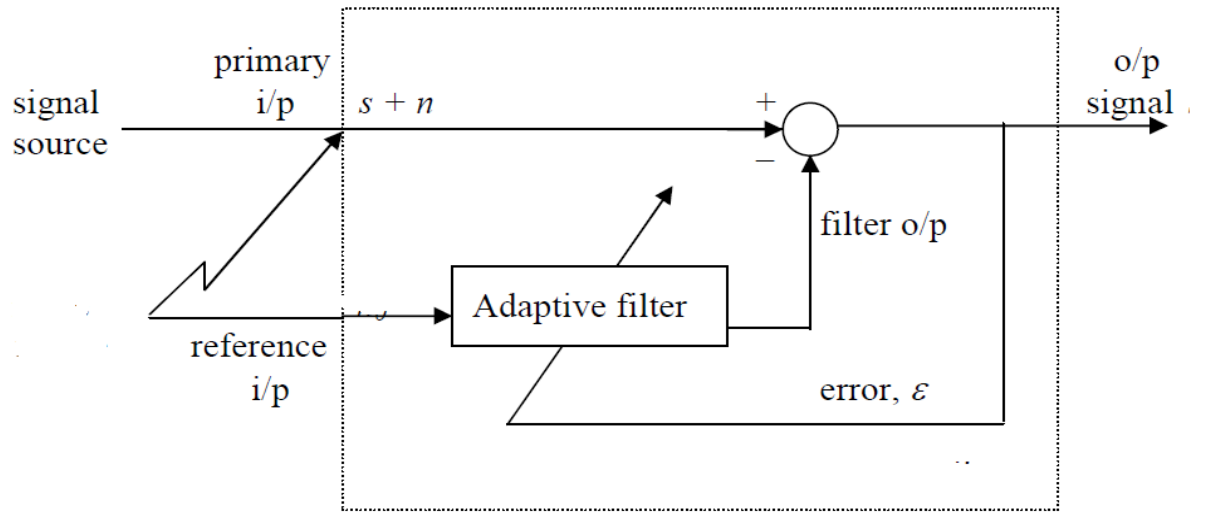


Figure 4.4: Block Diagram of Adaptive filter.

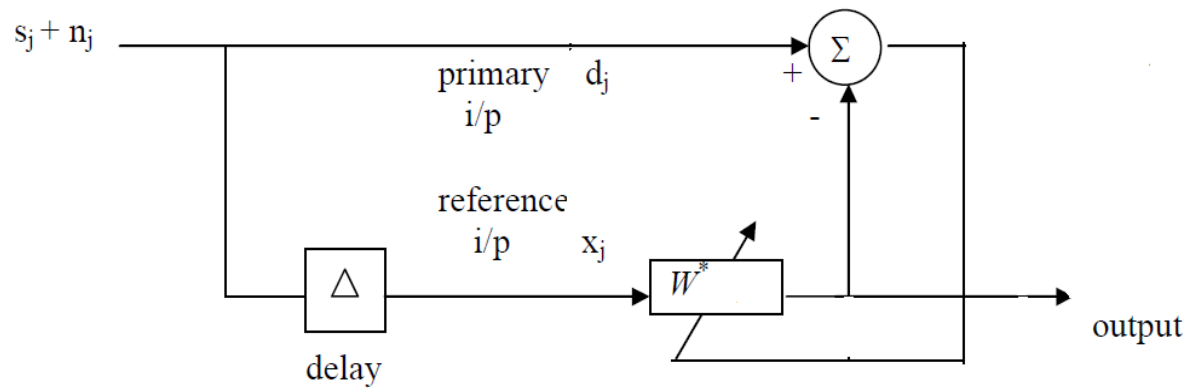


Figure 4.5: Block Diagram of the Proposed Method.

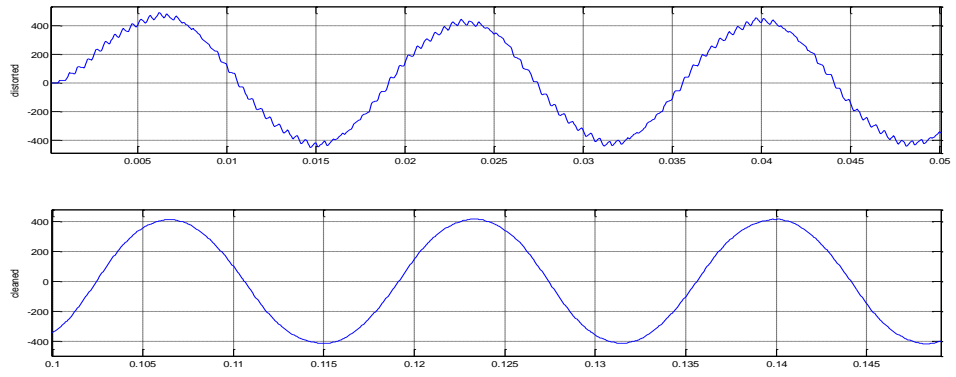


Figure 4.6: Distorted and Clean Current Signal Using LMS Algorithm When $\mu=1e-8$ and $M=120$.

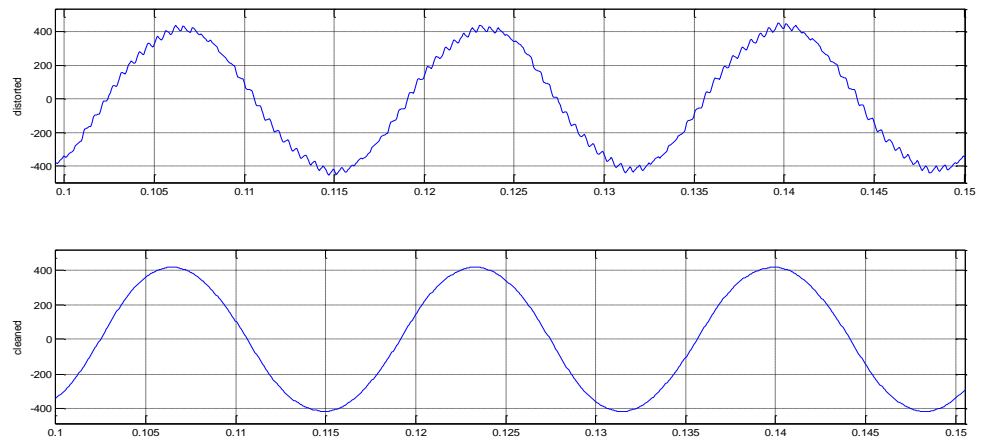


Figure 4.7: Distorted and Clean Current Signal Using NLMS Algorithm When $\mu=0.01$ and $M=120$.

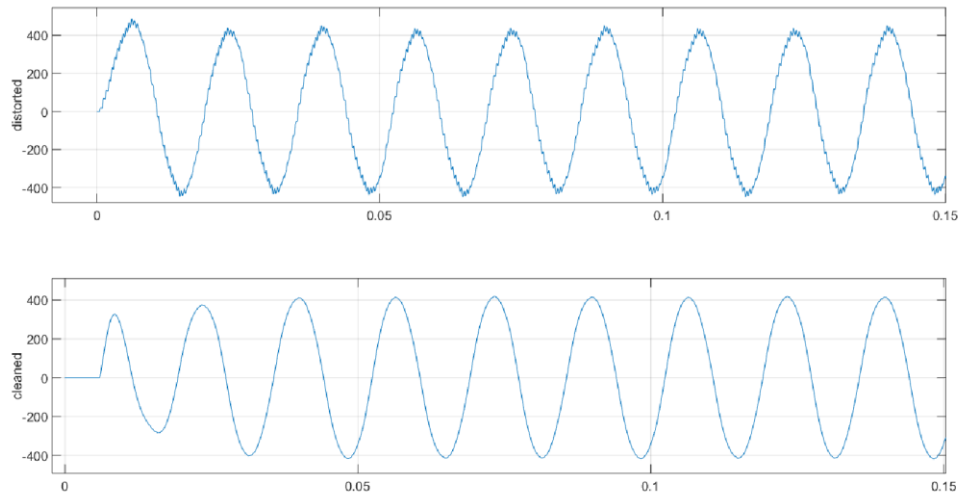


Figure 4.8: Distorted and Clean Current Signal Using Leaky LMS Algorithm When $\mu=2e-9$ and $M=120$.

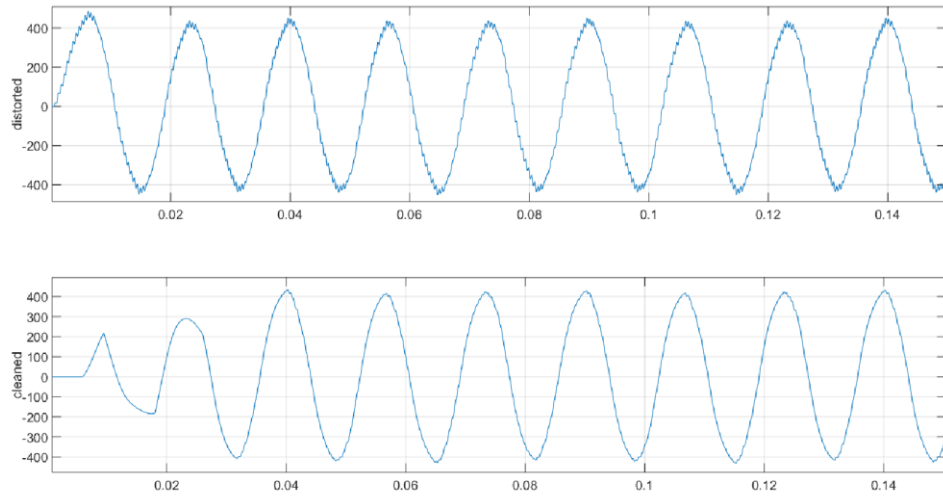


Figure 4.9: Distorted and Clean Current Signal Using Sign LMS Algorithm When $\mu=2e-9$ and $M=120$.

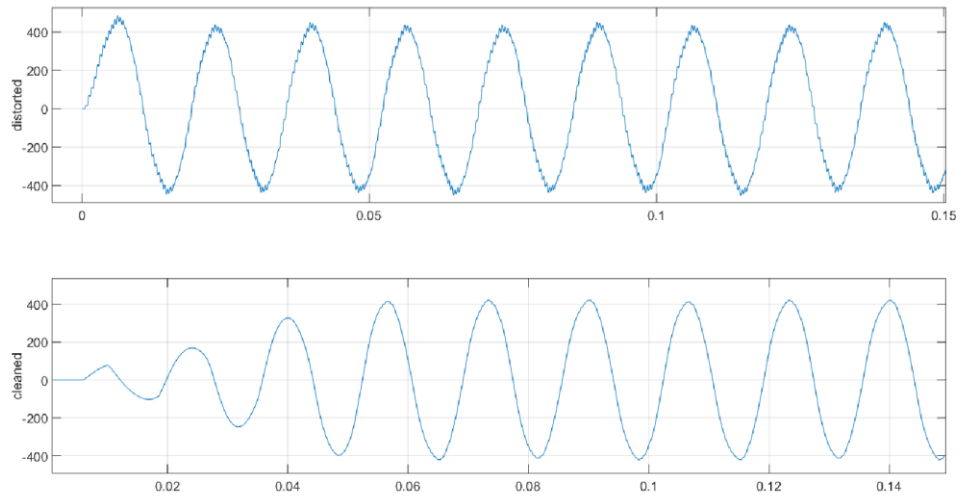


Figure 4.10: Distorted and Clean Current Signal Using Sign NLMS Algorithm When $\mu=1$ and $M=120$.

```

clc;
close all;
primary=V(:,1);
t=0:(0.5/length(primary)):0.5-(0.5/length(primary));
n=1:length(t);
d(n)=primary;%%%%%%%%d=primary is the distorted signal
x=zeros(1,length(t));
x(2:length(t))=d(1:length(t)-1); %x is the delayed version of the distorted signal
mu=0.00000001;
M=120;
N=length(x);
y=zeros(1,N);% initialized output of the filter
w=zeros(1,M)% initialized filter coefficient vector
e=zeros(1,N);% initialized output error of the filter
for n=M:N
    x1=x(n-1:n-M+1);% for each n the vector x1 is of length M with the elements from x in reverse order
    y(n)=w*x1';
    e(n)=d(n)-y(n);
    w=w+mu*e(n)*x1; % some books use other eq. which is w=w+2*mu*e(n)*x1;

```

```

end;

subplot(2,1,1);
plot(t,d);
ylabel('distorted');
grid on;
subplot(2,1,2);
plot(t,y);
ylabel('cleaned');
grid on;

```

Figure 4. 1: MATLAB Code for LMS Algorithm.

```

mu=0.1;
M=120;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
epsilon = 1e-2;
N=length(x);
y=zeros(1,N);% initialized output of the filter
w=zeros(1,M)% initialized filter coefficient vector
e=zeros(1,N);% initialized output of the filter

for n=M:N
    x1=x(n:-1:n-M+1);% for each n the vector x1 is of length M with the elements from x in reverse order
    y(n)=w*x1';
    e(n)=d(n)-y(n);
    factor = epsilon + norm(x1)^2;
    w = w + (mu/factor)*e(n)*x1; % NLMS update % some books use other eq.
end

```

Figure 4.12: MATLAB Code for NLMS Algorithm.

```

mu=0.01/5000000;
M=120;
gamma=0.1; % gamma is the leaking factor which is greater than zero but very very smaller than 1(0<gamma<<1)
N=length(x);
y=zeros(1,N);% initialized output of the filter
w=zeros(1,M)% initialized filter coefficient vector
e=zeros(1,N);% initialized output of the filter
for n=M:N
    x1=x(n:-1:n-M+1);% for each n the vector x1 is of length M with the elements from x in reverse order
    y(n)=w*x1';
    e(n)=d(n)-y(n);
    w=(1-mu*gamma)*w+mu*e(n)*x1; % some books use other eq. with 2 multiplied by mu;
end;

```

Figure 4.13: MATLAB Code for Leaky LMS Algorithm.

4.3 Distortion Reduction Using Wiener Filter

Weiner filter can be used to clean the distorted current signal from the inverter output. The steps mentioned in Poularikas and Ramadan textbook [38] were exactly followed. In their textbook, they provide detail method on how to use Wiener filter for noise cancellation. The same steps they described can be used for harmonics reduction since harmonics are nothing other than sum of noise. The book also provides MATLAB code that can be modified in order to fit our problem. Wiener filter gives better performance if normalized signal is used instead of the traditional signal. The MATLAB codes for this section are shown in Figures 4.14 - 4.15. The distorted and clean signal using Wiener filter are shown in Figure. 4.16. The THD of the output current signal using Wiener filter is

2.5%. Compare to adaptive filters, the performance of Wiener filter is much better in terms of convergence and stability but a little worse than adaptive filters in term of the powerful cleaning. It is very clear that the output signal using Wiener filter reaches the rated value in no time approximately but it still has some distortion in its peaks. Except the peaks, the output current signal seems to be very clear. If the load was changed in a certain way so the THD got increase Wiener filter is still be able to reduce it by more than 50%.

```

clc;
close all;
primary=V(:,1);
t=0:(0.5/length(primary)):0.5-(0.5/length(primary));
d=cos(2*pi*60*t);
% d=sin(0.1*pi*n);
% v=0.5*randn(1,511);
% x=d+v;
% v=cos(3*2*pi*60*t);

x=primary'/max(primary');
v=x-d;
M=120;
rd=aasamplebiasedautoc(d,M);
rv=aasamplebiasedautoc(v,M);

R=toeplitz(rd(1,1:M))+toeplitz(rv(1,1:M));
pdx=(rd(1,1:M));

w=inv(R)*pdx';
y=filter(w',1,x);
figure(1);
subplot(2,1,1);
plot(t,500*x/max(x),'b');
title('distorted');
grid on;
subplot(2,1,2);

```

```

plot(t,500*y/max(y),'b');
title('Weiner output');
grid on;

```

Figure 4.14: MATLAB Code for Weiner Filter [38].

```

function[r]=aasamplebiasedautoc(x,lg);

N=length(x);
for m=1:lg;
    for n=1:N+1-m;
        xs(m,n)=x(n-1+m);

    end;
end;
r1=xs*x';
r=r1'./N;

```

Figure 4.15: MATLAB Function for Weiner Filter [38].

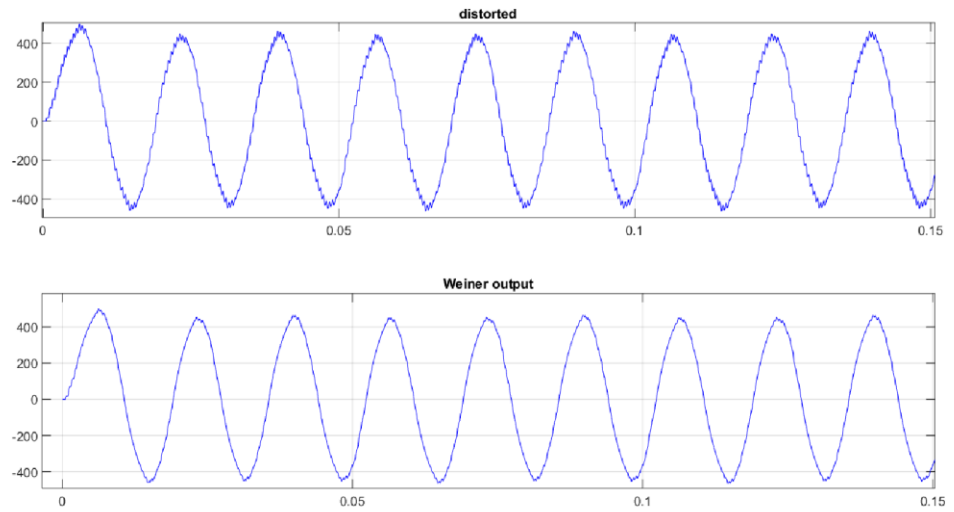


Figure 4.16: Distorted and Clean Current Signal Using Wiener Filter When $M=120$.

4.4 Distortion Reduction Using Kalman Filter

The third choice of harmonics reduction in this thesis is Kalman filter. Even if Kalman filter is very well known for prediction and estimation, there are some researches recently use Kalman filter for noise reduction. As mentioned earlier harmonics are nothing more than summation of noise. Hence Kalman filter can be used for harmonics reduction. In Kalman filter, the system has to be described in terms of state equations=mentioned in section 3.4. There are a lot of references and online sources giving state equations for different examples of systems. The matrices elements of the system must be selected to fit the system. The example used was one dimensional state matrix. The priori and posteriori

signals based on the modified MATLAB code is shown in Figure 4.17. The estimated clean signal using Kalman filter is shown in Figure 4.18.

```
clc;
close all;

primary=V(:,1);
t=0:(0.5/length(primary)):0.5-(0.5/length(primary));

nlen=length(t);
%Define the system.
a=1; %a=1 for a constant, |a|<1 for a first order system.
h=1;

%Define the noise covariances.
Q=0.01;
R=1;

%Preallocate memory for all arrays. Note that this is not really necessary
%but speeds up MATLAB a bit.
%However, it is necessary to come up with initial estimates (guesses) for
% 1) the state.
% 2) the a priori error.
x=zeros(1,nlen);
z=zeros(1,nlen);
xapriori=zeros(1,nlen);
xaposteriori=zeros(1,nlen);
residual=zeros(1,nlen);
papriori=ones(1,nlen);
paposteriori=ones(1,nlen);
k=zeros(1,nlen);

%Calculate the process and measurement noise.

%Initial condition on the state, x.
```

```

x_0=0;

%Initial guesses for state and a posteriori covariance.
xaposteriori_0=1;
paposteriori_0=1;

%Calculate the first estimates for all values based upon the initial guess
%of the state and the a posteriori covariance. The rest of the steps will
%be calculated in a loop.
%
%Calculate the state and the output
%x(1)=a*x_0+w(1);
x(1)=0;
%z(1)=h*x(1)+v(1);
z(1)=primary(1);
%Predictor equations
xapriori(1)=a*xaposteriori_0;
residual(1)=z(1)-h*xapriori(1);
papriori(1)=a*a*paposteriori_0+Q;
%Corrector equations
k(1)=h*papriori(1)/(h*h*papriori(1)+R);
paposteriori(1)=papriori(1)*(1-h*k(1));
xaposteriori(1)=xapriori(1)+k(1)*residual(1);

%Calculate the rest of the values.
for j=2:nlen,
    %Calculate the state and the output
    %x(j)=a*x(j-1)+w(j);
    x(j)=a*x(j-1);
    %z(j)=h*x(j)+v(j);
    z(j)=primary(j);
    %Predictor equations
    xapriori(j)=a*xaposteriori(j-1);
    residual(j)=z(j)-h*xapriori(j);
    papriori(j)=a*a*paposteriori(j-1)+Q;
    %Corrector equations
    k(j)=h*papriori(j)/(h*h*papriori(j)+R);
    paposteriori(j)=papriori(j)*(1-h*k(j));
    xaposteriori(j)=xapriori(j)+k(j)*residual(j);
end

```

```

j=1:nlen;
figure(1);
subplot(2,1,1);
plot(t,primary,'b');
ylabel('distorted'); grid on;
subplot(2,1,2);
plot(t,xapriori,'b'); hold on
plot(t,xaposteriori,'r');
legend('xapriori est.','xaposteriori est. ');
ylabel('estimated signal');
title('estimated and distorted signal'); grid on;
figure(2);
h1=stem(j,k,'b');
legend([h1(1)], 'kalman gain');
title('Kalman gain');
ylabel('Kalman gain, k');
set(gca,'XLim',xlim); %Set limits the same as first graph grid on;

```

Figure 4.17: MATLAB Code of Kalman Filter.

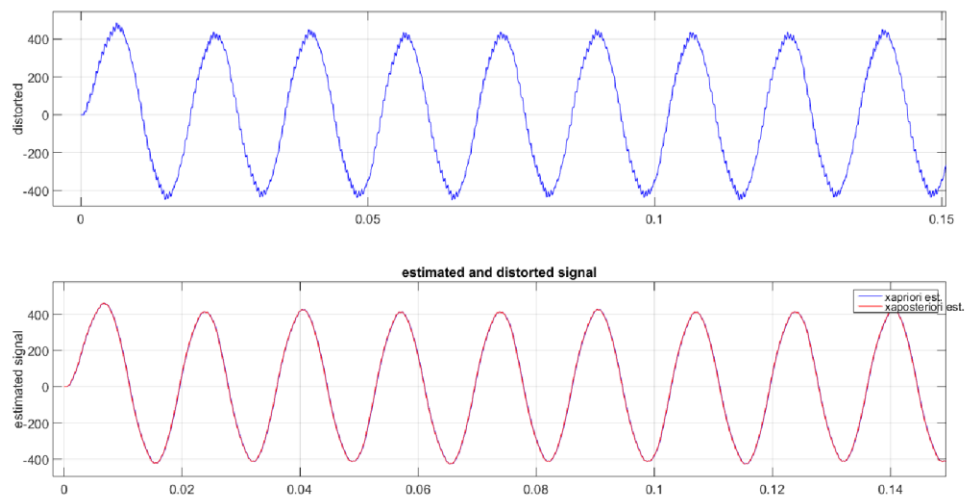


Figure 4.18: Distorted and Clean Current Signal Using Kalman Filter.

The performance of Kalman filter is very good in different aspects. It gives a stable signal with almost no distortion but since its iterative filter, it needs some time to reach its specified goal. The priori and the posteriori estimated signal seem to be identical, as shown in Figure 4.18. The THD of the output current signal using Kalman filter is 2.2%. If the load was changed to $R=10$ Ohm and $L= 1.592$ mille Henry, then THD would be 6.89% before the processing and 3.08% after the use of Kalman filter which means that Kalman filter is still able to reduce the THD by more than 50% as shown in Figure 4.19.

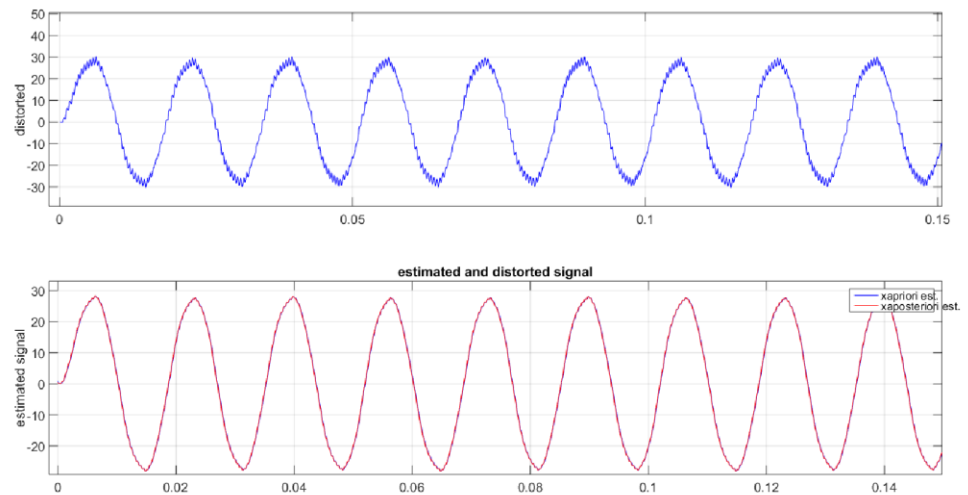


Figure 4.19: Distorted and Clean Current Signal Using Kalman Filter When $R=0.5$ and $L=1.592e-2$.

CHAPTER 5

CONCLUSIONS AND FUTURE WORKS

5.1 Conclusions

In this thesis, the quality of the output current signal of a single phase inverter was investigated as a case study. The output current signal has some distortion due to harmonics, which is a big issue not only in inverters but also in many power and power systems devices. There are a lot of causes for signal distortion such as harmonics, switches, nonlinear loads, and many more. The common way to clean the distorted signals are filters, such as passive and active filters. This thesis focused on how to clean distorted signal by using different kinds of filters. The used filters in this studies are adaptive, Weiner, and Kalman filters. In adaptive filter, five algorithms were used. LMS, NLMS, signed LMS, signed NLMS, and Leaky LMS algorithms were chosen as adaptive filtering techniques to clean the signal. They gave very good results in terms of harmonics reductions. Each one of them approaches the desired goals under different conditions, such as the step size, adaptation speed, etc. NLMS and signed NLMS gave the best performance as compared to other adaptive algorithms and they can reach the desired goal in shorter time and bigger step size.

Weiner filter was used to reduce the harmonics distortion in the current signal also. It gave much better performance than adaptiv filters in terms of convergence and stability but a little worse in terms of the powerful cleaning. The output signal from Weiner was very clean except some peaks which continue to have some distortion.

Kalman filter was used also in this thesis. It gave very good results in terms of harmonics reductions. Even if Kalman filter is very well-known for prediction and estimation, and noise cancellations. Kalman filtering was used in this thesis for harmonics reduction and it gave a very good performance. Hence, this point will increase the significant uses of Kalman filter.

In term of THD, Kalman filter gave the best performance as compared with adaptive and Wiener filters even if all of them can reduce the THD by more than 50%.

5.2 Future Works

1. During the adaption process the amplitude of the current waveform seems to be less than the amplitude of the rated current, an alternative solution to make this current reach the rated value as fast as possible has to be found.
2. Investigate the performance of proposed models using different loads.
3. In this research work DC-to-AC converter was used as a study case, the performance of the proposed models on different case studies may be investigated.
4. Practical implementation of these methods are needed.

BIBLIOGRAPHY

- [1] S. Rahmani, A. Hamadi and K. Al-Haddad, "A new combination of shunt hybrid power filter and thyristor controlled reactor for harmonics and reactive power compensation," in *Proceedings of IEEE Electrical Power & Energy Conference (EPEC)*, pp.1-6, 2009.
- [2] D. Rivas, L. Moran, J. W. Dixon and J. R. Espinoza, "Improving passive filter compensation performance with active techniques," *IEEE Transactions on Industrial Electronics*, vol. 50, pp. 161- 170, 2003.
- [3] E. KH. Almaita, "Adaptive radial basis function neural networks-based real time harmonics estimation and PWM control for active power filters," Ph.D. Dissertation, Western Michigan University, Kalamazoo, Michigan, USA, April 2012.
- [4] S. Haykin, *Neural Networks: A Comprehensive Foundation*. Second Edition, Prentice Hall, Upper Saddle River, New Jersey, 1999.
- [5] N. K. Kasabov, *Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering*. MIT Press, Cambridge, Massachusetts, 1996.
- [6] V. Blasko, L. Arnedo, P. Kashirsagar, and S. Dwari, "Control and elimination of sinusoidal harmonics in power electronics equipment: A system approach," in *Proceedings of IEEE Energy Conversion Congress and Exposition*, pp. 2827-2837, 2011.
- [7] V. Blasko, "A novel method for selective harmonic elimination in power electronic equipment," *IEEE Transaction on Power Electronics*, vol. 22, no.1, pp. 223-228, January, 2007.

- [8] S.V. Rode and S.A Ladhake, "An adaptive filter for harmonic elimination," *International Journal of Computer Science and Network Security*, vol. 10, no. 10, pp. 154-157, October, 2010.
- [9] A. Vashi, "Harmonic reduction in power system," M.sc thesis, California State University at Sacramento, California, USA, 2009.
- [10] A. A. Girgis, W. B. Chang and E. B. Makram, "A digital recursive measurement scheme for online tracking of power system harmonics," *IEEE Transactions on Power Delivery*, vol. 6, pp. 1153-1160, 1991.
- [11] S. Mariethoz and A. C. Rufer, "Open loop and closed loop spectral frequency active filtering," *IEEE Transactions on Power Electronics*, vol. 17, pp. 564-573, 2002.
- [12] T. Komrska, J. Žák and Z. Peroutka, "Control strategy of active power filter with adaptive FIR filter-based and DFT-based reference estimation," in *Proceedings of International Symposium on Power Electronics Electrical Drives Automation and Motion (SPEEDAM)*, pp.1524-1529, 2010.
- [13] B. Han, "Single-phase active power filter using FFT with harmonic phase-delay compensation," in *Proceedings of IEEE Power & Energy Society General Meeting (PES '09)*, pp. 1-6, 2009.
- [14] K. Borisov and H. Ginn, "A novel reference signal generator for active power filters based on recursive DFT," in *Proceedings of IEEE Twenty-Third Applied Power Electronics Annual Conference and Exposition (APEC 2008)*, pp. 1920-1925, 2008.

- [15] J. M. Maza-Ortega, J. A. Rosendo-Macias, A. Gómez-Expósito, S. Ceballos-Mannozi and M. Barrágan-Villarejo, "Reference current computation for active power filters by running DFT techniques," *IEEE Transactions on Power Delivery*, vol. 25, pp.1986-1995, 2010.
- [16] M. El-Habrouk, "Active power filters: A review," *IEE Proceedings Electric Power Applications*, vol. 147, pp. 403, 2002.
- [17] T. C. Green and J. H. Marks, "Control techniques for active power filters," *IEE Proceedings Electric Power Applications*, vol. 152, pp. 369-381, 2005.
- [18] E. F. Fuchs and M. A. S. Masoum, *Power Quality in Power Systems and Electrical Machines*, Elsevier Academic Press, 2008.
- [19] W. E. Kazibwe and M. H. Senduala, *Electric Power Quality Control Techniques*, New York: Van Nostrand Reinhold, 1993.
- [20] E. M. Stein, T. S. Murphy, *Harmonic Analysis: Real-Variable Methods, Orthogonality and Oscillatory Integrals*, Princeton University Press, New Jersey, 1993.
- [21] A. Zouidi, F. Fnaiech, K. Al-Haddad and S. Rahmani, "Adaptive linear combiners a robust neural network technique for on-line harmonic tracking," in *Proceedings of IEEE 34th Annual Conference of Industrial Electronics (IECON 2008)*, pp. 530-534, 2008.
- [22] Chen Ying and Lin Qingsheng, "New research on harmonic detection based on neural network for power system," in *Proceedings of The Third International Symposium on Intelligent Information Technology Application (IITA 2009)*, pp. 113-116, 2009.

- [23] G. W. Chang, Cheng-I Chen and Yu-Feng Teng, "Radial-Basis-Function-Based neural network for harmonic detection," *IEEE Transactions on Industrial Electronics*, vol. 57, pp. 2171-2179, 2010.
- [24] L. Malesani, P. Mattavelli and P. Tomasin, "High-performance hysteresis modulation technique for active filters," *IEEE Transactions on Power Electronics*, vol. 12, pp. 876-884, 1997.
- [25] V. M. Cardenas, C. Nunez and N. Vazquez, "Analysis and evaluation of control techniques for active power filters: Sliding mode control and proportional-integral control," in *Proceedings of IEEE Fourteenth Applied Power Electronics Annual Conference and Exposition (APEC 99)*, pp. 649-654, 1999.
- [26] O. Vodyakho, T. Kim and S. Kwak, "Comparison of the space vector current controls for shunt active power filters," in *Proceedings of IEEE 34th Annual Conference on Industrial Electronic (IECON 2008)*, pp. 612-617, 2008.
- [27] L. P. Ling and N. A. Azli, "SVM based hysteresis current controller for a three phase active power filter," in *Proceedings of IEEE National Power and Energy Conference (PECon 2004)*, pp. 132-136, 2004.
- [28] B. K. Bose, "An adaptive hysteresis-band current control technique of a Voltage-fed PWM inverter for machine drive system," *IEEE Transactions on Industrial Electronics*, vol. 37, no.5, pp. 402-408, 1990.
- [29] Li Jun and Wang Dazhi, "Study and simulation of a novel hysteresis current control strategy," in *Proceedings of the Second International Conference on Intelligent Computation Technology and Automation (ICICTA '09)*, pp. 306-309, 2009.

- [30] K. Bose, "Neural network applications in power electronics and motor drives- An introduction and perspective," *IEEE Transactions on Industrial Electronics*, vol. 54, pp. 14-33, 2007.
- [31] Q. Quan and K. Cai, "A New viewpoint on the internal model principle and its application to periodic signal tracking," in *Proceedings of the 8th World Congress on Intelligent Control and Automation*, July 6-9, 2010, Jinan, China.
- [32] M.H. Rashid, *Power Electronics: Devices, Circuits, and Applications*, Fourth Edition, Pearson Educational Limited, 2014.
- [33] S.V. Rode and S.A. Ladhake, "A modified method for harmonic elimination," *International Journal of Computer and Electrical Engineering*, vol. 3, no. 4, pp. 493-496, August, 2011.
- [34] I. Batarseh, *Power Electronic Circuits*. John Wiley, New York, 2004.
- [35] L.L. Grigsby, *Power Systems*, CRC Press, 2007
- [36] A.H. Sayed, *Fundamental of Adaptive Filtering*, John Wiley & Sons, New Jersey, 2008.
- [37] S. Haykin, *Adaptive Filter Theory*, Fourth Edition, Prentice Hall, 2001.
- [38] A.D. Poularikas and Z. M. Ramadan, *Adaptive Filtering Primer with MATLAB*, Taylor& Francis Group, New York, 2006.
- [39] K. Mayyas and T. Aboulnasr, "Leaky LMS algorithm: MSE analysis for Gaussian data," *IEEE Transactions on Signal Processing*, vol.45, no.4, pp.927-934, April 1997.

- [40] R. E. Deakin, "The Kalman filter: A look behind the scene," in *Proceedings of Victorian Regional Survey Conference*, Mildura, 23-25, June 2006.
- [41] D. Simon, "Using nonlinear Kalman filtering to estimate signals," *Embedded Systems Design*, vol.19, no. 7, pp.38-53, 2006.
- [42] D. Jwo, M. Chen, C. Tseng, and T. Cho, "Adaptive and nonlinear Kalman filtering for GPS navigation processing," *Journal of Recent Advances and Applications In Kalman Filter*, vol.14, 2009.
- [43] N.C. Yang, C. H. Hsieh, and C.M. Kuo, "Kalman filtering based motion estimation for video coding," in *IEEE Workshop on Signal Processing Systems*, pp. 129 -134, 2008.
- [44] S. Gannot, "Speech processing utilizing the Kalman filter," *IEEE Instrumentation & Measurement Magazine*, vol.15, no.3, pp.10-14, June 2012.
- [45] V. Oikonomou, A. Tzallas, S. Konitsiotis, D. Tsalikakis, and D. Fotiadis, "The use of Kalman filter in biomedical signal processing," *Journal of Recent Advances and Applications In Kalman Filter*, 2009.
- [46] R. Kazemi, A. Farsi, M.G. Ghaed, and M. Karimi-Ghartemani, "Detection and extraction of periodic noises in audio and biomedical signals using Kalman filter," *Elsevier Signal Processing Journal*, vol. 88, no. 8, pp. 2114-2121, August, 2008.
- [47] MATLAB version 15.a. Natick, Massachusetts: The MathWorks Inc., 2015.