SYNCHRONISED FILTERING OF THE FUNDAMENTAL COMPONENT OF VOLTAGE AND CURRENT IN POWER LINE

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CERTIFICATE

It is certified that Mr. Rohan Kumar Koudinya, Roll No.8664, student of M.E, Control and Instrumentation, Department of Electrical Engineering, Delhi College of Engineering, has submitted the dissertation entitled **"Synchronised Filtering of The Fundamental Component Of Voltage And Current In Power Line"**, under my guidance towards partial fulfillment of the requirements for the award of the degree of Master of Engineering (Control & Instrumentation Engineering).

This dissertation is a bonafide record of project work carried out by him under my guidance and supervision. His work is found to be good and his discipline impeccable during the course of the project.

I wish him success in all his endeavors.

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ABSTRACT

Power system has witnessed increase in power electronics load which operates on switching of the devices. This has brought the increase in undesirable frequency component in the power lines in the form of current and in the voltage. Analysis, measurement, compensation and operation control becomes difficult amidst such conditions. Filter as the name suggests, filters out the undesirable frequency component of a signal. Filtering of noise from signal is being used for signal processing applications. The synchronised extraction of fundamental frequency signal component has always been considered a daunting task for application engineers to advocate application of signal processing and power apparatus to Electrical systems. The main goal of this work is to develop a synchronised and adaptive filter that can track the fundamental component of current and voltage received from the power line, amidst high and low frequency components without delay.

The current or voltage signal obtained from the power line feeding power to power electronics converters is distorted with harmonics and or loss of frequency component, besides this the uncertainties in power line; change of frequency, phase and dynamics of load makes the filtering process very complex and difficult. The proposed work aims at extraction of the fundamental component of source current and voltage amidst harmonic distortion through a tunable synchronized filter scheme. The input voltage waveform is filtered through tunable adaptive filter to produce delay less fundamental frequency component. Analysis design and development of new filter system is presented in this thesis. Simulation, as well as the generation of the test signals, is realized in the Matlab Simulink environment.

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LIST OF SYMBOLS

k	Sampling instant
x(k)	Input applied to the adaptive filter
d(k)	Desired signal
y(k)	Output of the adaptive filter
e(k)	Estimation error.
w(k)	Filter weight
n(k)	Noise signal
s(k)	Input signal
α	Adaptive tuning variable for low pass filter
ω_c	Filter cut-off frequency
h(k)	Filter impulse response
H(z)	Filter transfer function
μ	The step-size for filter tuning algorithm
$\hat{\psi}(k)$	Rate of change of filter error function
$\hat{\Psi}(z)$	Z-transform of filter error function
υ	Adaptive low pass filter performance function
Ω_c	Passband edge frequency
W(n)	FIR filter window function
Θ	Phase angle difference of filter output
Φ	Power spectrum density

CHAPTER - I

INTRODUCTION

1.1 GENERAL

The proliferation of power electronics converter has opened the floodgates for flow of harmonics, subharmonics into the power system. This distortion in currents easily spread through voltage distortion at point of common coupling due to drop of voltage across line impedance. Many modern electrical equipments fail to operate due to these distortions, moreover control circuits based on zero crossing suffer badly due to multiple zero crossings of the zero signal. It is therefore becomes mandatory for control circuits to filter the distortions from the voltage signal without causing any phase delay. The following sections discuss the development of new synchronised filtering system for many control applications for power system, drives and control systems. The following chapters in thesis deals with origin of the problem of frequency distortion in power lines and the need of base/synchronizing signal is discussed followed by solution of the problem with the help of Adaptive tunable filters, which is the central idea of the thesis. In the later section the layout of the thesis is presented.

1.2 PROBLEM FORMULATION

The increased use of nonlinear load has significantly increased the amount of harmonics in power systems. The harmonics sub harmonics, and interharmonics are the undesired signal components that are commonly present in the current and voltage waveforms. As an application, many electronic circuits, control circuits, power electronic converters, which uses these voltage or current signals as feedback signals needs following , to achieve requisite performance. Moreover, circuits based on zero crossing detection suffer very badly due to multiple zero crossings. It becomes mandatory for all control circuits operating under such environment must filter out undesired signals without producing any phase delay. To attenuate the harmonics, active power filters are often used. Shunt active filters, the most widely used system configuration, is suitable for damping the harmonic currents. While the series active filter is suitable for damping the harmonic voltages. Shunt active filters are used to generate the current that is equal but opposite to the harmonic currents in the current waveform. Therefore, only the fundamental current would be delivered by mains supply. However, successful control of the shunt active filter requires an accurate and delay less current reference.

Digital band pass filters and the instantaneous power theory have been used previously as the primary methods to obtain the desired current reference. However, conventional digital band pass filters are sensitive to frequency variations. Thus, harmful phase shift occurs as the frequency changes from the nominal value. On the other hand, instantaneous power theory is based on complex voltage and current transforms as well as their inverse transforms. Further, in non symmetrical situations, the instantaneous power theory can not provide an accurate reference for active power filters, because it is based on exact three phase symmetry.

Also, the unwanted distortion of the input voltage and line currents is of particular concern when the incoming voltage/current signals are sampled, and then used in a post processed form as templates to generate gating signals. The concern stems from the acquisition or generation of time-varying aliased signals within the bandwidth of a control system. Aliasing or under sampling generates undesirable sub harmonics, interharmonics, and, under certain circumstances, control loop instabilities. In some processes, the upper sampling or switching frequency is restricted by external constraints. In contrast, the line frequency places an upper bound on the sampling frequency for line-commutated thyristor bridges. Converters or inverters generate either directly or indirectly through feedback, sub harmonics and interharmonics. Sub harmonics and interharmonics other than sideband frequencies of carrier-modulated signals can be avoided by adopting a synchronized sampling process adaptive filter scheme.

1.3 SCOPE OF THE WORK

Our objective is to obtain a base sampling/synchronised signal, which is common to the system in use to generate templates for gating signals from phase voltage waveforms. The desired signal is obtained by getting the input signal pass through the proposed filtering scheme; in the present work one such efficient filtering system based on adaptive algorithms is presented named Synchronised Adaptive Filter (SAF). This filter tracks the fundamental frequency variations in the line-frequency while maintaining satisfactory band-pass filtering of the signal without delay. Also, it can be used for the generation of distortionless gating or synchronization signal.

1.4 CONFIGURATION OF THE SYNCHRONISED ADAPTIVE FILTER(SAF)

The fundamental component in power line and sub fundamental frequency components can be extracted with the application of an adaptive low pass filter, to filter the harmonic components present in the signal, the filter will adapt to the low pass signal present at the input side. This filter will be a low pass of first order **IIR** type. The adaptive filter is based on the stochastic gradient algorithm for the adaption of the filter coefficients. The error signal is taken as the output of the filter itself and the recursive algorithm designed here is supposed to maximize the error/output. Then the signal is processed through the **Adaptive High pass** filter connected in tandem with the adaptive low pass filter to remove the sub-harmonics present, if any in the input signal, the filter structure used is the **FIR** and the design is based on the window technique using a Blackman window.

Since the presence of filters cause undue phase lag it becomes necessary to have a predictive filter in the last stage of the filter design, to compensate the delays caused due to the presence of adaptive low pass filter and high pass filter, in the initial stages.

The scheme of things can be depicted in the block diagram form as follows:

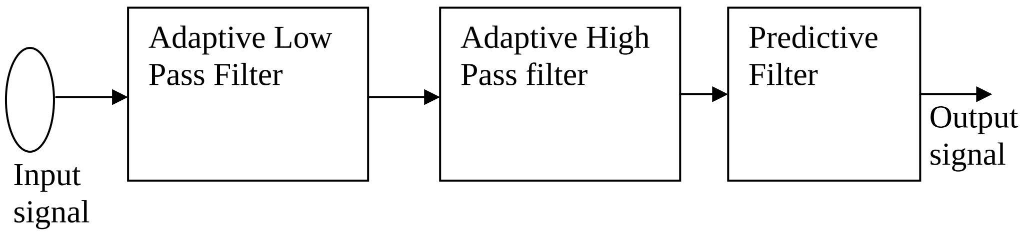

Figure1.1 block diagram of the proposed filter scheme

1.4.1 Concepts of Filtering

When one talks about signal, the noise and unwanted signal becomes its integral part. In real world, every signal is accompanied with noise that degrades the quality of the signal and corrupts the information the original signal carries. It may not be possible to completely remove the noise from the signal as the two may have overlapping spectrum. The noise can not be removed from the signal completely; one has to live with it. However, it may be possible to reduce the degree of noise level to the extent that the information carried by the original signal can be recovered or reconstructed. This is possible by filtering the spectrum occupied by the required signal and filtering out the spectrum of unwanted signal and noise.

A filter is a system that removes the unwanted signals from the original signal, or shapes the incoming signal in a much more desired form, that may carry useful information and the characteristics are nearer to the desired one. Knowing that a signal will always be accompanied by noise and unwanted interference our attempt would be to minimize the noise or at least reduce to an acceptable level by appropriate signal processing techniques.

This minimum level of noise depends on the user requirements. As shown in fig 1.2, any signal fed to an instrument can be represented as combination of two signals; one which is required by for the further processing and the other, which is an unwanted part of the signal referred as noise/interference.

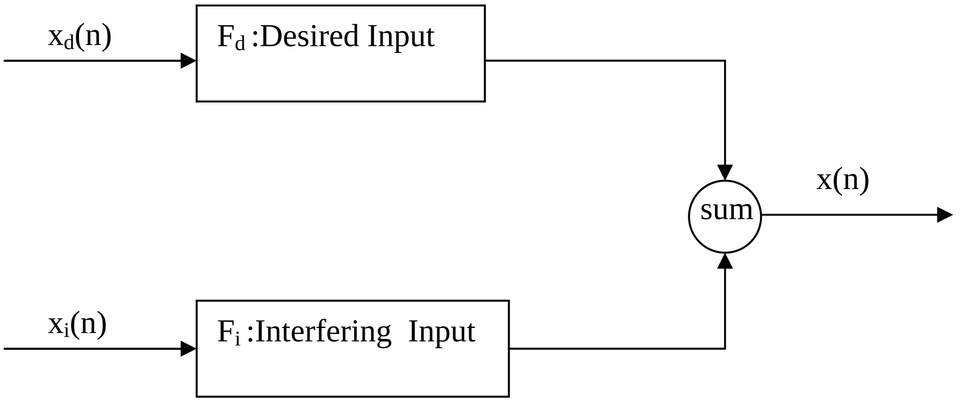

Fig.1.2 The input signal in terms of desired and interfering inputs

$\mathbf{F_d}$ shows the desired input and $\mathbf{F_i}$ is the interfering noise or undesired signal to input.

In case the signals are in analog form, analog filters provide an easy and economic solution, but the drawback is the lack of precision and stability. The digital systems on the other hand provide a desired precision and stability at the cost of complexity. So the analog signals are required to be processed in the digital form leading in to the exciting and challenging field of “Digital Signal Processing” and digital filter form a part of this processing. Apart from stability and precision, the digital processing of signal also gives us flexibility of reconfiguring the whole process via software and thereby providing us a programmability feature. Hence the programmable digital filters.

1.4.2 Digital Filter

The digital filter, as the name suggests, filters a digital signal to extract the desired signal and to reduce noise. As in real world most of the processes are represented by continuous signal, their processing in digital form would require digitization of the signal with the help of Analog to Digital converter (ADC) of an optimal resolution. After the processing, the signal can be converted back to analog/continuous form with the aid of Digital to Analog converter (DAC). The question may arise now, why to use the digital filters?

A digital filter is programmable, i.e. its operation is determined by a program stored in the processor's memory. This means the digital filter can easily be changed without affecting the circuitry (hardware). An analog filter can only be changed by redesigning the filter circuit. Digital filters are easily designed, tested and implemented on a general-purpose computer or workstation. The characteristics of analog filter circuits (particularly those containing active components) are subject to drift and are dependent on temperature. Digital filters do not suffer from these problems, and so are extremely stable with respect both to time and temperature. Unlike their analog counterparts, digital filters can handle low frequency signals accurately. As the speed of DSP technology continues to increase, digital filters are being applied to high frequency signals in the RF (radio frequency) domain, which in the past was the exclusive preserve of analog technology.

Digital filters are very much more versatile in their ability to process signals in a variety of ways; this includes the ability of some types of digital filter to adapt to changes in the characteristics of the signal. Fast DSP processors can handle complex combinations of filters in parallel or cascade (series), making the hardware requirements relatively simple and compact in comparison with the equivalent analog circuitry.

It is easy to handle digital filters as compared to an analog filter. For an analog filter we are required to use amplifiers but their precision is grounded by the use of other components. These are more sensitive to environmental changes, while the digital filter will remain unaffected. We therefore, got all the advantage of digital technique over that of analog processing. The digital systems are bound to have some quantization errors that appear due to limited word length of A/D converter, which can be kept to an acceptable level by using optimal word length.

1.5 ORGANISATION OF THE THESIS

The thesis is organized into six chapters; the introduction of each is as follows:

Chapter 1: This chapter gives the problem identification, the proposed solution, the objective of the study and the filter fundamentals. At last a brief description of the thesis layout is given.

Chapter 2: This chapter reviews previous research done relevant to the extraction of fundamental component in power line, and the extraction of base sampling/synchronizing signal which is common to the system. The research involves various methods for each stage of the solution; some of them have been utilized in this thesis.

Chapter 3: An introduction of the Adaptive filters is provided in this chapter. The need of the adaptive filters, various types of them and their applications in various fields are discussed. Together with the design procedure of the adaptive filters using different techniques.

Chapter 4: This chapter introduces the layout of the project, the different modules and its implementation

Chapter 5: The results from the outcome of adaptive filters are provided using MATLAB, detailing the dependency of procedure on previous steps. Then achievement of goal is discussed.

Chapter 6: Conclusion about the efficiency of digital signal processing system for active filter current reference generation is presented.

CHAPTER -II

LITERATURE REVIEW

2.1 GENERAL

The extraction of the harmonicless frequency component from the source line is always a desirable characteristic. It had been a challenge for the application engineers to remove the harmonic and subharmonic content from the input signal and obtain the harmonicless fundamental frequency component of voltage or current signal from the power line. Several filtering techniques have been proposed by application engineers over a period of time to obtain the distortion less component from the power line, they have been discussed here which gives insight to the problem taken and makes way for the filtering technique discussed in the dissertation.

2.2 FREQUENCY DISTORTION IN POWER LINE

The increased use of nonlinear loads during the last few decades has significantly increased the amount of harmonics in power systems. The harmonics, subharmonics, and interharmonics are the undesired signal components that are commonly present in the current and voltage waveforms. To attenuate the harmonics, active power filters are often used. Shunt active filter, the most widely used system configuration, is suitable for damping harmonic currents [15]**,** while the series active filter is suitable for damping the harmonic voltages. Shunt active filter is used to generate the current that is equal but opposite to the harmonic currents in the current waveform. Therefore, only the fundamental current would be delivered by the mains supply. However, successful control of the shunt active filter requires an accurate and delay less current reference. Digital bandpass filters [16] and the instantaneous power theory [17] have been used previously as the primary methods to obtain the desired current reference. However, conventional digital bandpass filters are sensitive to frequency variations. Thus, harmful phase shift occurs as the frequency changes from the nominal value. On the other hand, instantaneous power theory is based on complex voltage and current transforms as well as their inverse transforms. Further, in non-symmetrical situations, the instantaneous power theory cannot provide an accurate reference for active power filters, because it is based on exact three-phase symmetry.

Tai Ling Leung [1] proposed two solutions to obtain the current reference for the filter the first scheme uses a pure FIR predictor, and the second one consists of an FIR part enhanced with a single feedback loop. The high versatility of the proposed adaptive predictor is due to the lack, or small number of fixed coefficients in the filter structure.

2.2.1) Adaptive Predictor

Adaptive filter must be predictive to compensate for the delay introduced by the measurement instrumentation and to allow interpolation in the final processing stage. The forward prediction step is proportional to the number of unit delays that are cascaded with the LMS algorithm based FIR filter.

In this approach, there is the advantage of the automatic, or data driven, adjustment of the FIR filter coefficients. The resulting filter predicts the line-frequency sinusoid one step ahead regardless of the possible frequency variation. The coefficients of the FIR filter are computed using the LMS-algorithm**.** This algorithm has the desired characteristics of robustness and computational simplicity.

2.2.2) Adaptive Predictor with a Feedback Loop

An FIR filter of length 22 was used to construct the adaptive predictor in the previous section. Here, an advantageous feedback loop is introduced into the FIR structure. By applying this approach, the computational complexity can be reduced by decreasing the FIR filter length, and simultaneously increase the harmonics attenuation capability of the filtering system.

In the year 1998 Sami Valivita came up with the “Delay less Method to Generate current reference for Active filters” [3] in which it was discussed the Active power filters are used to eliminate ac harmonic currents by injecting equal but opposite compensating currents. Successful control of active filters requires, among other things, an accurate current reference. In this paper, a multistage adaptive filtering system was introduced which generates the current reference delaylessly and accurately. The filter structure combines a low-pass prefilter and an adaptive predictive filter, making it possible to extract the sinusoidal active current from the distorted waveform without harmful phase shift, even when the frequency and amplitude alter simultaneously. Although active filters are typically used to compensate for the supply harmonics, where the fundamental frequency remains almost constant, it was shown that this filter structure can also be applied in applications where the frequency alters rapidly.

The given structure consists of the prefilter at the first stage, so that the harmonics of the fundamental are filtered at the initial stage itself. The output of the low pass filtered is then fed to an adaptive predictor filter to account for the delays caused by the low pass filter at the initial stage.

In the year 1999 David Nedeljkovic presented a method to generate the current reference [5] for the active power filter. The three phase active power filter structure given by him generated the required current reference.
Adaptive notch filters have been used for the extraction of fundamental component of the power signal [8]. M. Karimi-Ghartemani discussed various forms of the notch filters presented in his work “estimation of power system frequency using adaptive notch filter”.

2.3 BASE SAMPLING/SYNCHRONIZATION SIGNAL GENERATION

The increasing use of static power converters in industrial and utility applications has resulted in unwanted distortion of the input voltage and line currents [2]. This distortion is of particular concern when the incoming voltage and current signals are used as templates to generate synchronization signals for

(i) Line commutated converter; such as phase controlled rectifiers, voltage followers and cycloconverters,
(ii) Forced commutated converters that use either one of the following two modulation strategies; a carrier signal with a low switching to fundamental frequency ratio; selective harmonic elimination or when signals obtained from the network are Fourier decomposed using a digital Fourier transform and then used in a control loop.

In both cases, access to an event generating signal which is synchronized to the fundamental component of the incoming signal or a multiple frequency thereof is required. Improper synchronization can lead to the generation of undesirable subharmonics, uncharacteristic harmonics and control loop instabilities. More recently, some industrial users have been requesting an improved ride-through capability in the event of network disturbances, and/or access to an alternative energy source if the source of primary power fails. In the former case, it is common to provide energy storage to meet a minimum ride through requirement and to detect the state of the network. Disturbances which exceed specific bounds result in the initiation of a shut-down sequence. In the latter case, transfer between the primary source and secondary source is accomplished by means of a static transfer switch. For both of the cases it is important to correctly and quickly discriminate between a disturbance which should or should not initiate an action. This discrimination is made easier if a reference template waveform representing the time varying fundamental component of the power source can be generated and used for comparison purposes.

Francis P. Dawson in the year 1999 had used the PLL based approach for the synchronization signal extraction in the paper "Variable-Sample-Rate Delayless frequency adaptive digital filter for synchronised signal acquisition and sampling"[4]. The synchronization signal is obtained in three steps:

(i) extraction of fundamental component of an incoming distorted signal
(ii) generating a zero-crossing detection signal with the fundamental component
(iii) applying the zero crossing signal to the PLL.

2.4 CONCLUSION

Thus, from the above study a strong need of a Synchronised adaptive filter arose for the extraction of the fundamental component of current and voltage signal in power line, which could as well serve as the base or synchronization signal generator for the system. In this thesis a synchronised adaptive filtering scheme is presented to serve the aforesaid purposes.

CHAPTER -III

ADAPTIVE FILTERS: PRINCIPLE OF OPERATION AND APPLICATIONS

3.1 GENERAL

An adaptive filter is a filter containing coefficients that are updated by some type of adaptive algorithm to improve or somehow optimize the filter's response to a desired performance criterion. In general, adaptive filters consist of two basic parts: the filter which applies the required processing on the incoming signal which is to be filtered; and an adaptive algorithm, which adjusts the coefficients of that filter to somehow improve its performance.

Adaptive filtering techniques are necessary considerations when a specific signal output is desired but the coefficients of that filter cannot be determined at the outset. Sometimes this is because of changing line or transmission conditions. An adaptive filter is one which contains coefficients that are updated by an adaptive algorithm to optimize filter response to the desired performance criterion.

The overall structure for an adaptive filter is shown below in Figure. The incoming signal, x(n), is filtered (or weighted) in a digital filter to produce an output, y(n). The adaptive algorithm will continuously adjust the coefficients, or tap weights, in the filter to minimize the error, e(n), between the filtered output, y(n), and a signal representing the desired response of the filter, d(n). Selection of the desired response, d (n), of the filter is sometimes the most difficult step and can dramatically affect the success of the adaptive filter.

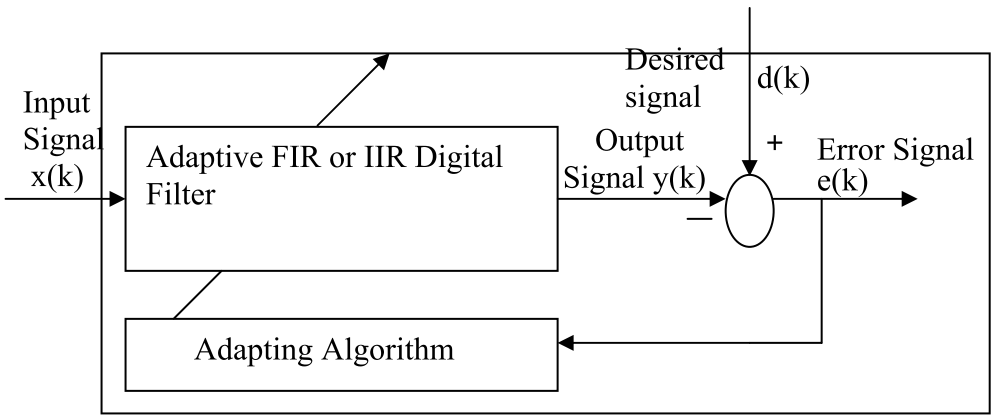

Figure 3.1 - General Form of an Adaptive Filter

Where,

$e(k) = d(k) - y(k)$

$y(k) = Filter\{ x(k),w(k) \}$

$w(k+1) = w(k) + e(k)*x(k)$

An adaptive FIR or IIR filter designs itself based on the characteristics of the input signal to the filter and a signal which represent the desired behavior of the filter on its input. Designing the filter does not require any other frequency response information or specification. To define the self learning process the filter uses, we select the adaptive algorithm used to reduce the error between the output signal y(k) and the desired signal d(k). When the LMS performance criteria for e(k) has achieved its minimum value through the iterations of the adapting algorithm, the adaptive filter is finished and its coefficients have converged to a solution. Now the output from the adaptive filter matches closely the desired signal d(k). When we change the input data characteristics, sometimes called the filter environment, the filter adapts to the new environment by generating a new set of coefficients for the new data. Notice that when e(k) goes to zero and remains there you achieve perfect adaptation; the ideal result but not likely in the real world.

3.2 APPROACHES TO THE DEVELOPMENT OF LINEAR ADAPTIVE FILTER

There is no unique solution to the linear adaptive filtering problem. Rather, we have a “kit of tools” represented by variety of recursive algorithms, each of which offers desirable features of its own. The challenge facing the user of adaptive filtering is, first, to understand the capabilities and limitations of various adaptive filtering algorithms and, second, to use the understanding in the selection of appropriate algorithm for the application at hand.

Basically, we may identify two distinct approaches for deriving recursive algorithms for the operation of linear adaptive filters.

3.2.1 Stochastic Gradient Approach

The stochastic gradient approach uses a tapped delay line, or transversal filter, as the structural basis for implementing the linear adaptive filter. For the case of stationary inputs, the cost function, also referred as the index of performance, is defined as the mean-square error (i.e., the mean square value of the difference between the desired response and the transversal filter output). The cost function is precisely a second order function of the tap weights in the transversal filter. The dependence of the mean-square error on the known tap weights may be viewed to be in the form of a multidimensional paraboloid (i.e. a "punch bowl") with a uniquely defined bottom, or minimum point. The tap weights corresponding to the minimum point of the surface define the optimum Wiener solution.

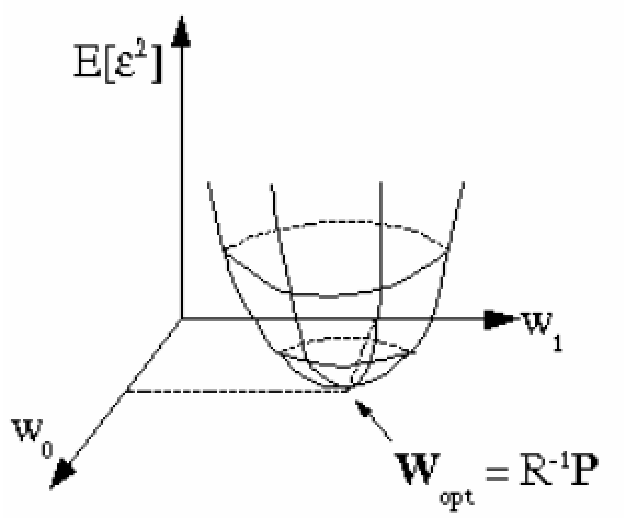

Figure 3.2 Wiener Filter coefficients as a function of error

To develop a recursive algorithm for updating the tap weights of the adaptive transversal filter, we proceed in two stages; first, we use an iterative procedure to solve the Wiener-Hopf equations (i.e., the matrix equation defining the optimum Wiener solution); the iterative procedure is based on the method of the steepest descent. This method requires the use of a *gradient vector*, the value of which depends on two parameters: the correlation matrix of the tap inputs in the transversal filter and the cross-correlation vector between the desired response and the same tap inputs. Next, we use instantaneous values for these correlations, so as to derive an estimate for the gradient vector, making it assume a stochastic character in general.

The resulting algorithm is widely known as the least-mean-square (LMS) algorithm, the essence of which, for the case of transversal filters operating on real-valued data, may be described as

$$\begin{pmatrix} updated\_value \\ of\_tap-weight \\ vector \end{pmatrix} = \begin{pmatrix} old\_value \\ of\_tap-weight \\ vector \end{pmatrix} + \begin{pmatrix} learning \\ rate \\ parameter \end{pmatrix} \begin{pmatrix} tap-input \\ vector \end{pmatrix} \begin{pmatrix} error \\ signal \end{pmatrix}$$

Where the error signal is defined as the difference between some desired response and the actual response of the transversal filter produced by the tap-input vector.

The LMS algorithm is simple and yet capable of achieving satisfactory performance under the right conditions. Its major limitations are a relatively slow rate of convergence and sensitivity to variations in the condition number of the correlation matrix of the tap inputs.

In a nonstationary environment, the orientation of the error-performance surface varies continuously with time. In this case, the LMS algorithm has the added task of continually tracking the bottom of the error-performance surface. Indeed, tracking will occur, provided that the input data vary slowly compared with the learning rate of the LMS algorithm.

3.2.2 Least Square Estimation

The second approach to the development of linear adaptive filtering algorithm is based on the method of least squares. According to this method, we minimize a cost function or an index of performance that is defined as the sum of weight error squares, where the error or residual is itself defined as the difference between some desired response and the actual filter output. The method of least squares may be formulated with block estimation or recursive estimation in mind. In block estimation, the input data stream is arranged in the form of blocks of equal length (duration), and the filtering of input data proceeds on a block-by-block basis. In recursive estimation, on the other hand, the estimates of interest (e.g., tap weights of a transversal filter) are *updated* on a sample-by-sample basis.

Recursive least-square (RLS) *estimation* may be viewed as a special case of Kalman filtering. A distinguishing feature of Kalman filter is the notion of *state,* which provides a measure of all the inputs applied to the filter up to a specific instant of time. Thus at the heart of the Kalman filtering algorithm, we have a recursion that may be described as:

$$\begin{pmatrix} updated\_value \\ of\_the \\ state \end{pmatrix} = \begin{pmatrix} old\_value \\ of\_the \\ state \end{pmatrix} + \begin{pmatrix} KalmanGain \\ \ \end{pmatrix} \begin{pmatrix} Innovation \\ Vector \end{pmatrix}$$

Where the *innovation vector* represents new information put into the filtering process at the time of the computation.

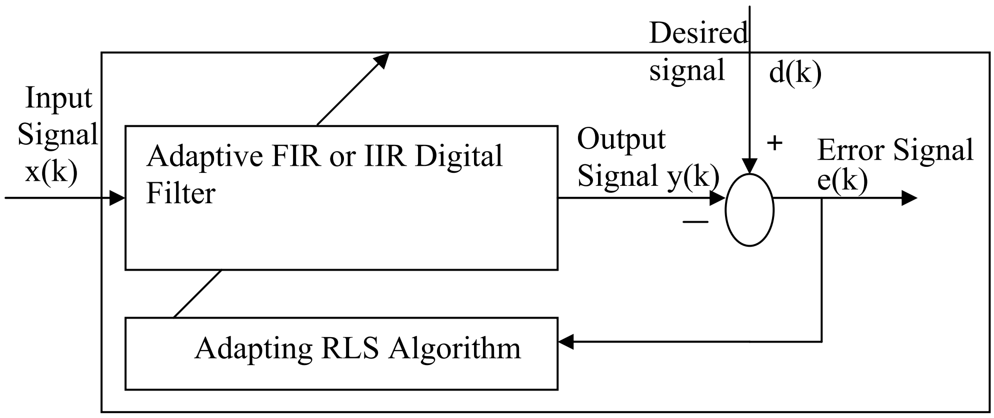

Figure 3.3 Block diagram of adaptive RLS Filter

e(k) = d(k) – y(k),

y(k) = filter {x(k),w(k)},

w(k+1) = w(k) + e(k)*f{d(k),x(k)}

If LMS algorithms represent the simplest and most easily applied adaptive algorithms, the recursive least squares (RLS) algorithms represents increased complexity, computational cost, and fidelity. In performance, RLS approaches the Kalman filter in adaptive filtering applications, at somewhat reduced required throughput in the signal processor. Compared to the LMS algorithm, the RLS approach offers faster convergence and smaller error with respect to the unknown system, at the expense of requiring more computations. In contrast to the least mean squares algorithm, from which it can be derived, the RLS adaptive algorithm minimizes the total squared error between the desired signal and the output from the unknown system. The signal flow graph (or model) for the RLS adaptive filter system is given in fig.3.3. The signal paths and identifications are the same whether the filter uses RLS or LMS. The difference lies in the adapting portion. Within limits, any of the adaptive filter algorithms can be used to solve an adaptive filter problem by replacing the adaptive portion of the application with a new algorithm. Examples of the sign variants of the LMS algorithms demonstrated this feature to demonstrate the differences between the sign-data, sign-error, and sign-sign variations of the LMS algorithm. One interesting input option that applies to RLS algorithms is not present in the LMS processes a forgetting factor, λ, that determines how the algorithm treats past data input to the algorithm. When the LMS algorithm looks at the error to minimize, it considers only the current error value. In the RLS method, the error considered is the total error from the beginning to the current data point. Said another way, the RLS algorithm has infinite memory all error data is given the same consideration in the total error. In cases where the error value might come from a spurious input data point or points, the forgetting factor lets the RLS algorithm reduce the value of older error data by multiplying the old data by the forgetting factor. Since $0< \lambda < 1$, applying the factor is equivalent to weighting the older error. When $\lambda = 1$, all previous error is considered of equal weight in the total error. As approaches zero, the past errors play a smaller role in the total. For example, when $\lambda = 0.9$, the RLS algorithm multiplies an error value from 50 samples in the past by an attenuation factor of $0.950 = 5.15 \times 10^{-3}$, considerably de-emphasizing the influence of the past error on the current total error.

We may classify the recursive least-squares family of linear adaptive filtering algorithms into three distinct categories, depending on the approach taken:

3.2.2.1 the standard RLS algorithm

They assume the use of a transversal filter as the structural basis of the linear adaptive filter. The algorithm enjoys the same virtues and suffers from the same limitations as the standard Kalman filtering algorithm. The limitations include the lack of numerical robustness and excessive computational complexity. Indeed, it is these two limitations that have prompted the development of the other two categories of RLS algorithm.

3.2.2.2 square-root RLS algorithms

They are based on QR-decomposition of the incoming data matrix. Two well-known techniques for performing this decomposition are the Household transformation and the *Given rotation*. The resulting linear adaptive filters are referred to as square-root adaptive filters, because, in a matrix sense, they represent the square root forms of the standard RLS algorithm.

3.2.2.3 fast RLS algorithm.

The standard RLS algorithm and square, root RLS algorithm have a computational complexity that increases as the square of M, where M is the number of adjustable weights (i.e., the number of degree of freedom) in the algorithm. Such algorithms are referred to as O (M^2) algorithms, where O (.) abbreviates “order of”. There is a strong motivation to modify RLS in such a way that the complexity assumes an O (M) form. This is achievable by virtue of the inherent redundancy in the structure of input data matrix and, second, by exploiting the redundancy through the use of linear least-squares prediction in both the forward and backward directions. The resulting algorithm is known collectively as fast RLS algorithms; they combine the characteristic of recursive linear least-square estimation with O (M) computational complexity.

3.3 FOUR CLASSES OF OPERATION

The ability of an adaptive filter to operate satisfactorily in an unknown environment and track time variations of input statistics makes the adaptive filter a powerful device for signal processing and control applications. An input vector and a desired response are used to compute an estimation error, which is in turn used to control the values of a set of adjustable filter coefficients. The difference between the various applications of adaptive filtering arises in the manner in which the desired response is extracted. In this context we may distinguish four basic classes of adaptive filtering applications, as depicted below:

3.3.1 System Identification

The notion of mathematical model is fundamental to science and engineering. In the class of application dealing with identification, an adaptive filter is used to provide linear model that represents the best fit (in some sense) to an unknown plant. The plant and the adaptive filter are driven by the same input. The plant output supplies the desired response for the adaptive filter. If the plant is dynamic in nature, the model will be time varying. Applications include, such as the response of an unknown communications channel or the frequency response of an auditorium, to pick fairly divergent applications. Other applications include echo cancellation and channel identification. In the figure, the unknown system is placed in parallel with the adaptive filter.

Clearly, when e(k) is very small, the adaptive filter response is close to the response of the unknown system. In this case the same input feeds both the adaptive filter and the unknown. When the unknown system is a modem, the input often represents white noise, and is the sound we hear from the modem when we log in to the Internet service provider.

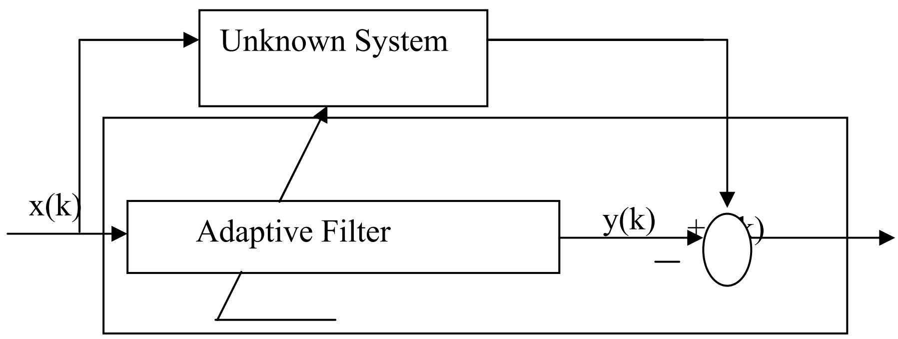

Figure 3.4: Adaptive Filter for FIR Filter Identification

Where,

x (k) =input applied to the adaptive filter;

y (n) =output of the adaptive filter;

d (k) = desired response;

e (k) = d-y = estimation error.

3.3.2 Noise Cancellation

One of the most common practical applications of adaptive filters is noise cancellation. We simulated the situation in which the adaptive filter needed to remove a time varying noise from a desired speech signal. This could be a model for a person speaking on a cell phone in a car where his voice is corrupted by noise from the car's engine. The adaptive filter is used to cancel unknown interference contained (alongside an information-bearing signal component) in a primary signal, with the cancellation being optimized in some sense. The primary signal serves as the desired response for the adaptive filter. A reference (auxiliary) signal is employed as the input to the filter.

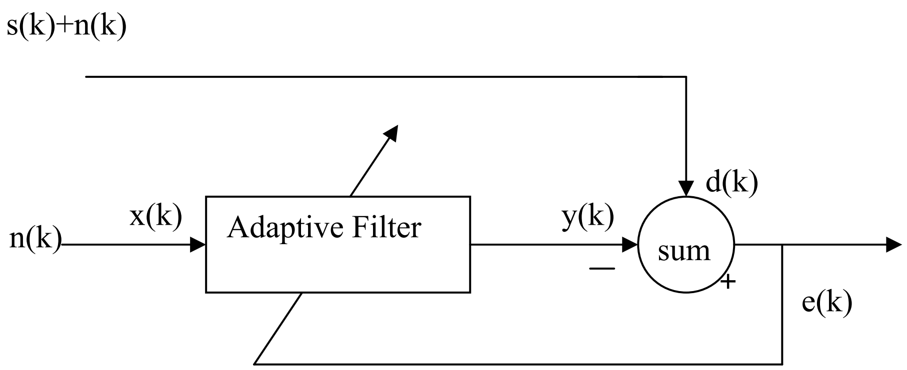

Figure3.5: Noise Cancellation adaptive filter system

3.3 Inverse System Identification

By placing the unknown system in series with your adaptive filter, your filter becomes the inverse of the unknown system when e(k) gets very small. As shown in the figure the process requires a delay inserted in the desired signal d(k) path to keep the data at the summation synchronized. Adding the delay keeps the system causal.

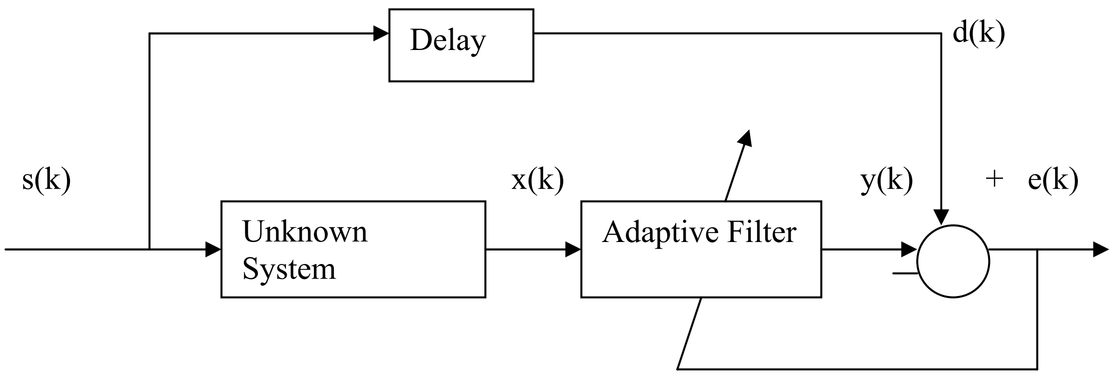

Figure3.6: Determining an Inverse Response to an Unknown System

Without the delay element, the adaptive filter algorithm tries to match the output from the adaptive filter (y (k)) to input data (x (k)) that has not yet reached the adaptive elements because it is passing through the unknown system. In essence, the filter ends up trying to look ahead in time. As hard as it tries, the filter can never adapt: e(k) never reaches a very small value and your adaptive filter never compensates for the unknown system response. And it never provides a true inverse response to the unknown system. Including a delay equal to the delay caused by the unknown system prevents this condition.

So long as the input noise to the filter remains correlated to the unwanted noise accompanying the desired signal, the adaptive filter adjusts its coefficients to reduce the value of the difference between y(k) and d(k), removing the noise and resulting in a clean signal in e(k). Notice that in this application, the error signal actually converges to the input data signal, rather than converging to zero

3.3.4 Prediction

Predicting signals may seem to be an impossible task, without some limiting assumptions. Assume that the signal is either steady or slowly varying over time, and periodic over time as well.

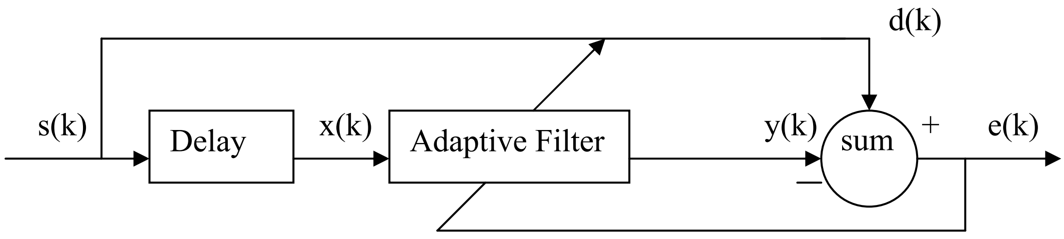

Figure3.7: Predicting Future Values of a Periodic Signal

Accepting these assumptions, the adaptive filter must predict the future values of the desired signal based on past values. When s (k) is periodic and the filter is long enough to remember previous values, this structure with the delay in the input signal, can perform the prediction. We might use this structure to remove a periodic signal from stochastic noise signals.

3.4 CONCLUSION

Finally, most systems of interest contain elements of more than one of the four adaptive filter structures. Carefully reviewing the real structure may be required to determine what the adaptive filter is adapting to.

CHAPTER -IV

MODELING, ANALYSIS AND DESIGN OF SYNCHRONOUS ADAPTIVE FILTER

4.1 GENERAL

This chapter deals with the modeling of the Synchronised Adaptive Filter (SAF) system and its various modules. The first stage consists of an Adaptive low pass filter**,** which is based on **IIR** filter structure. The adaptation algorithm together with the analysis and design of the filter structure is presented. In the second stage an adaptive high pass **FIR** filter structure is analysed with the window technique is presented. In the final stage an adaptive predictor filter*,* to remove any phase-delays introduced by the previous stages is compensated from the filtered signal. The filter design uses a Least Mean Square (LMS) algorithm for the coefficients updation.

4.2 CONFIGURATION OF SYNCHRONOUS ADAPTIVE FILTER (SAF)

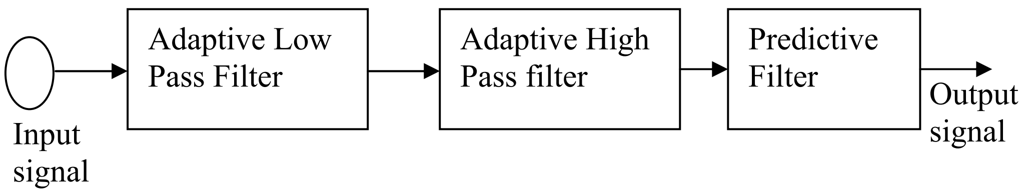

Figure 4.1 Block Diagram Of SAF

The synchronous adaptive filter is built in three stages, with a low-pass adaptive filter placed at the initial stage. The adaptive low pass filter is designed with the IIR configuration of first order with a single tunable variable. The filter transfer function of first order IIR filter is given below:

$$H(z) = \frac{1+z^{-1}}{1+\alpha z^{-1}}$$

As the signal is fed to the filter the low pass filter tracks the low frequency component of the input signal, based on the gradient algorithm and the adaptive variable settles for the suitable value so as to give the required low pass characteristic to the filter.
The filter frequency response can be depicted as in fig 4.1:

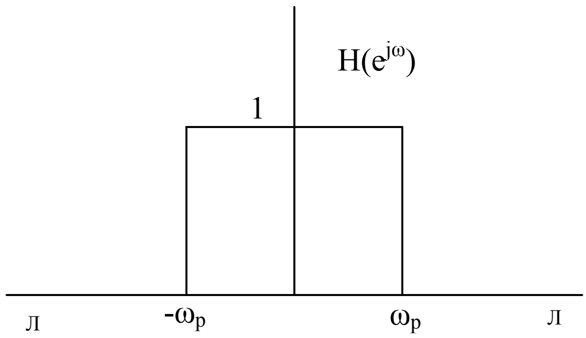

Figure4.2 the frequency response of low pass filter

The output of the low pass filter is then passed through the high pass filter that is of simple FIR type. The high pass filter, filters out the subharmonics present in the input signal thus leaving only the fundamental frequency component of input signal.
The high pass filter has the frequency response shown below in fig.4.2:

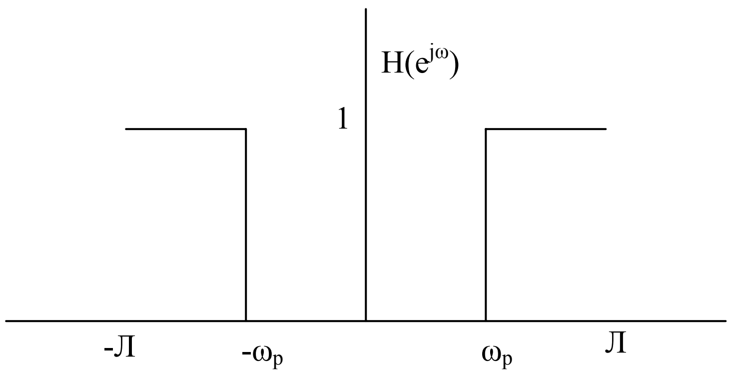

Figure 4.3 the frequency response of an ideal high pass filter

Thus the adaptive low pass filter and the high pass filter connected in series gives the characteristic of an adaptive band pass filter whose passband edge frequency varies as the input voltage or current signal varies in frequency. Thus the resulting configuration behaves like an adaptive band pass filter.The combined frequency response of our filter structure comes out to be as shown below in fig 4.4:

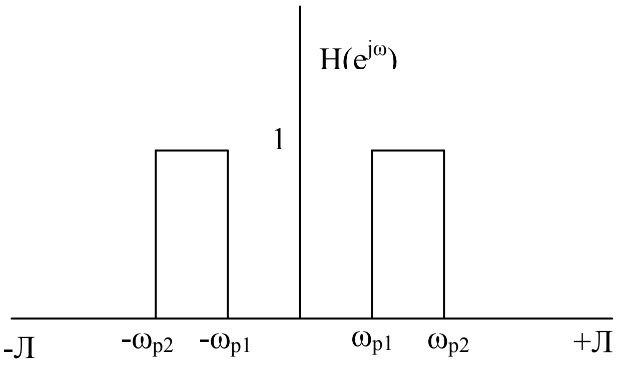

Figure 4.4 Adaptive band pass filter

The final stage is to design a predictor filter in order to remove the phase delay caused at the initial filtering stages of low-pass and high pass filter. The design of adaptive predictor filter is based on the LMS algorithm. The three stage of filters discussed so far are now dealt with I detail in the following sections.

4.3 ADAPTIVE LOW PASS FILTER

It is often required to eliminate high frequency noise added to lowpass signals such as speech sounds. For efficient noise reduction, we need lowpass filters whose cutoff frequencies are equal to edge frequencies of the lowpass signals. In subband coding information is efficiently compressed by assigning more bits to the bands whose power spectrum is large. We may use lowpass and higbpass filters whose cutoff frequencies are equal to boundary frequencies of high and low power regions to enhance the efficiency of the bits assignment in the subband coding. It is found from the above two examples that we often need to know passband-edge frequencies of lowpass signals.

Only bandpass and bandstop types of adaptive infinite impulse response (IIR) filters have been reported. For example, adaptive notch filters detect the center frequency and the bandwidth of narrow-band noise in wide-band signals to enhance the signal-to-noise ratio. These adaptive **IIR** filters use the stochastic gradient algorithm. They search the extremum of Mean Square Error (MSE) of the output of the adaptive IIR notch filter. The stochastic gradient algorithm can update the filter coefficient without any computation of MSE, and is suitable for real-time processing. In the case of estimating the bandwidth of unknown narrowband bandpass signals by adaptive notch filters, the extrema of differentiated MSEs are searched or weighted transfer functions are used, because MSEs evaluated from the original transfer function are the increasing functions of adaptive coefficients and have no extremum.

The proposed filter finds a method for detecting the unknown passband-edge frequencies of lowpass signals using adaptive lowpass filters (ALFs). ALFs are a kind of variable lowpass filters whose cutoff frequencies are adaptively varied by their single coefficients. The filter coefficient is controlled to equalize the cutoff frequency to the unknown passband-edge frequency of lowpass signal. As ALF we start with the simplest first-order IIR lowpass filter. Stochastic gradient algorithm is also used as adaptive algorithm. At first, it is shown that MSEs of simple IIR lowpass filters have no extrema because they are increasing functions with respect to adaptive coefficient. This means that stochastic gradient algorithms cannot be applied. To solve this problem, a weighting function to be multiplied with the first-order IIR lowpass transfer function is introduced so that MSEs have extrema at the passband-edge frequency. Stochastic gradient algorithms can then be applied to the derived transfer functions to adaptively detect the passband edge frequencies of lowpass signals. It also shows structures to realize the proposed ALFs on the basis of lattice structures. In order to evaluate the accuracy of the detection of passband-edge frequencies, a performance function is defined. It confirms the convergency of the proposed algorithms by simulations, and investigates the step size of stochastic gradient algorithms.

4.3.1 Variable Low Pas Filter

We use a variable lowpass filter whose transfer function is

$$H(z) = \frac{1+z^{-1}}{1+\alpha z^{-1}} * \left(\frac{1+\alpha}{2}\right) \tag{4.1}$$

Where the filter coefficient α varies the cutoff frequency ω_C. The relation between α and ω_C is given by Eq.(2)

$$\alpha = \frac{\tan\frac{\omega_c}{2} - 1}{\tan\frac{\omega_c}{2} + 1} \qquad (-1 \le \alpha \le 1) \tag{4.2}$$

Eq (4.2) shows that the larger α is, the wider the passband is.

When the input signal and impulse response of the variable filter are represented by x (k) and h(k), respectively, its output signal e(k) is given by

$$e(k) = h(k) * x(k) \tag{4.3}$$

where * denotes a convolution operation. Thus, the power spectrum density $\Phi(e^{j\omega})$of e(k) is described by

$$\Phi_{ee}(e^{j\omega}) = \left| H(e^{j\omega}) \right|^2 \Phi_{xx}(e^{j\omega}) \tag{4.4}$$

Where $\Phi_{xx}(e^{j\omega})$ is the power spectrum density of x(k). We use e(k) as an error function, but in this case the error is *to* be maximized. MSE of e(k) is used as an objective function to detect the passband-edge frequencies of lowpass signals. The MSE is given by

$$MSE = E[\, e^2(k)] \tag{4.5}$$

The auto correlation function

$$R_{ee}(n) = E[e(k)e(k+n)] \tag{4.6}$$

can be reduced to

$$R_{ee}(0) = E[e^2(k)]$$

$$= \frac{1}{2\pi}\int_{-\pi}^{\pi} \Phi_{ee}(e^{j\omega})d\omega$$

by applying the Parseval's relation. Thus, considering Eq.(4.4), we obtain

$$MSE = \frac{1}{2\pi}\int_{-\pi}^{\pi} \left| H(e^{j\omega}) \right|^2 \Phi_{xx}(e^{j\omega})d\omega \tag{4.9}$$

Here, we input an ideal low pass signal

$$X(e^{j\omega}) = \begin{cases} A & |\omega| \le \Omega_c \\ 0 & otherwise \end{cases}$$

(4.10)

into the variable low pass filter, where $\mathbf{\Omega_c}$ is the passband edge frequency. From Eq.(4.9), we obtain

$$\text{MSE} = \frac{A^2}{\pi}\int_0^{\Omega_c}\left|H(e^{j\omega})\right|^2 d\omega \tag{4.11}$$

The derivative of MSE is

$$\text{MSE} = \frac{A^2}{\pi}\int_0^{\Omega_c}\frac{\partial}{\partial\alpha}\left|H(e^{j\omega})\right|^2 d\omega \tag{4.12}$$

Differentiating $|H(e^{jw})|^2$ with respect to α , we obtain

$$\frac{\partial}{\partial\alpha}\left|H(e^{j\omega})\right|^2 = \frac{4(1-\alpha^2)\tan^2\frac{\omega}{2}}{\left\{(1+\alpha)^2+(1-\alpha)^2\tan^2\frac{\omega}{2}\right\}} \ge 0 \tag{4.13}$$

Since Eq.(4.12) and (4.13) show that the MSE is an increasing function, the MSE has no extremum.

4.3.2 Gradient Algorithm

As MSEs of conventional IIR lowpass filters are increasing functions with respect *to* a, we cannot find the values of a which correspond to the passband-edge frequencies by using the following gradient algorithm,

$$\alpha_{k+1} = \alpha_k + \mu\frac{\partial}{\partial\alpha}MSE \tag{4.14}$$

where μ is a step size constant. In order that MESS have such extrema, we introduce a weighting function *f(a)* to be multiplied to the transfer function *H (Z)* of the first-order IIR lowpass filter. We represent a multiplied transfer function by V (z) = *f (a) H (z)* . Then, *to* adaptively detect the passband-edge frequencies we can apply gradient algorithms to a weighted MSE which corresponds to *V(z).* The weighted MSE is represented by MSE_V. From Eq.(9), we can express MSEv as

$MSEv = f^2(\alpha)MSE.$ (4.15)

If the variable lowpass filter is ideal, MSE curve becomes piecewise linear. So in the neighborhood of α = **-1,** we can approximate MSE by a linear function *MSE* = $c_1(1 + \alpha)$. Then the derivative of *MSEv* is calculated as

$$\frac{\partial}{\partial\alpha} MSE_v = c_1 f(\alpha)\left\{2(1+\alpha)\frac{\partial}{\partial\alpha} f(\alpha) + f(\alpha)\right\} \quad (4.16)$$

By solving the differential equation $\frac{\partial}{\partial\alpha}$ *MSEv* = 0, we obtain

$$f(\alpha) = \frac{C}{\sqrt{1+\alpha}} \quad (4.17)$$

Here, differentiating $|V(e^{jw})|^2$ with respect to α, we obtain

$$\frac{\partial}{\partial\alpha}\left|V(e^{j\omega})\right|^2 = C^2 \frac{4\tan^2\frac{\omega}{2} - (1+\tan^2\frac{\omega}{2})(1+\alpha)^2}{\left\{(1+\alpha)^2 + (1-\alpha)^2\tan^2\frac{\omega}{2}\right\}^2} \quad (4.18)$$

We find $\frac{\partial}{\partial\alpha}|V(e^{jw})|^2 \,|_{\alpha=-1} > 0$ and $\frac{\partial}{\partial\alpha}|V(e^{jw})|^2 \,|_{\alpha=1} < 0$ from eq(4.18).
It is now clear that $\frac{\partial}{\partial\alpha}$ *MSEv* becomes zero at a certain value of α between -1 and 1, i.e,
MSE_v has an extremum.

However, the curves do not seem to have extrema.This is caused by the fact that the approximation of the MSE is valid only in the neighborhood of ***a*** = -1. Then, we compensate the weighting function by rationalization at the center of the region of ***a.*** The well-known approximation (1 + z)" = 1+nz, gives

$$f(\alpha) = \frac{C}{\sqrt{1+\alpha}} \quad (4.19)$$

We also reduce Eq.(4.19) to a polynomial in consideration of hardware implementation. Thus, the weighting function becomes

$$f(\alpha) \approx C(1-\frac{1}{2}\alpha)^2 \tag{4.20}$$

4.3.3 Design Of Adaptive Low Pass Filter

In the previous section we modified the MSEs which are used as the objective functions for the gradient algorithms. However, it is difficult to calculate statistical values like MSEs in real-time processing, because the calculations of MSEs require average operations in the whole time domain. To implement the gradient algorithms, we adopt approximated ones named as stochastic gradient algorithms which use the instantaneous values of error functions instead of MSEs. The stochastic gradient algorithms are given by

$$\alpha_{k+1} = \alpha_k + \mu\frac{\partial}{\partial\alpha}e^2(k) \tag{4.21}$$

$$= \alpha_k + 2\mu e(k)\hat{\psi}(k), \tag{4.22}$$

Where $\hat{\psi}$ (k) is $\frac{\partial}{\partial\alpha}$e(k). When we express the z-transform of e(k) by E(z), it is given by

$$E(z) = V(z)X(z) \tag{4.23}$$

Then $\hat{\Psi}(z)$ which is the z-transform of $\hat{\psi}$ (k) is given by

$$\hat{\Psi}(z) = \frac{\partial}{\partial\alpha}E(z) = \frac{\partial}{\partial\alpha}V(z)X(z) \tag{4.24}$$

Thus the filter Ψ (z) = $\frac{\partial}{\partial\alpha}$V(z) is given by

$$\Psi(z) = (\frac{1}{2}\alpha - 1)\frac{1+z^{-1}}{1+\alpha z^{-1}}.\left\{\frac{3}{2}\alpha + (1-\frac{1}{2}\alpha)(1+\alpha)\frac{z^{-1}}{1+\alpha z^{-1}}\right\}. \tag{4.25}$$

We set C = **2** in Eq.(4.20) for simplicity. We can detect the passband-edge frequencies by the filters V (z) and $\hat{\psi}$ *(z).* The structure of the **ALF** is given in Fig 4.2, where a lattice structure is used to realize V (z) and $\hat{\psi}$ (z). The transfer function of the lattice structures is

$$\frac{1+z^{-1}}{1+\alpha z^{-1}}. \tag{4.26}$$

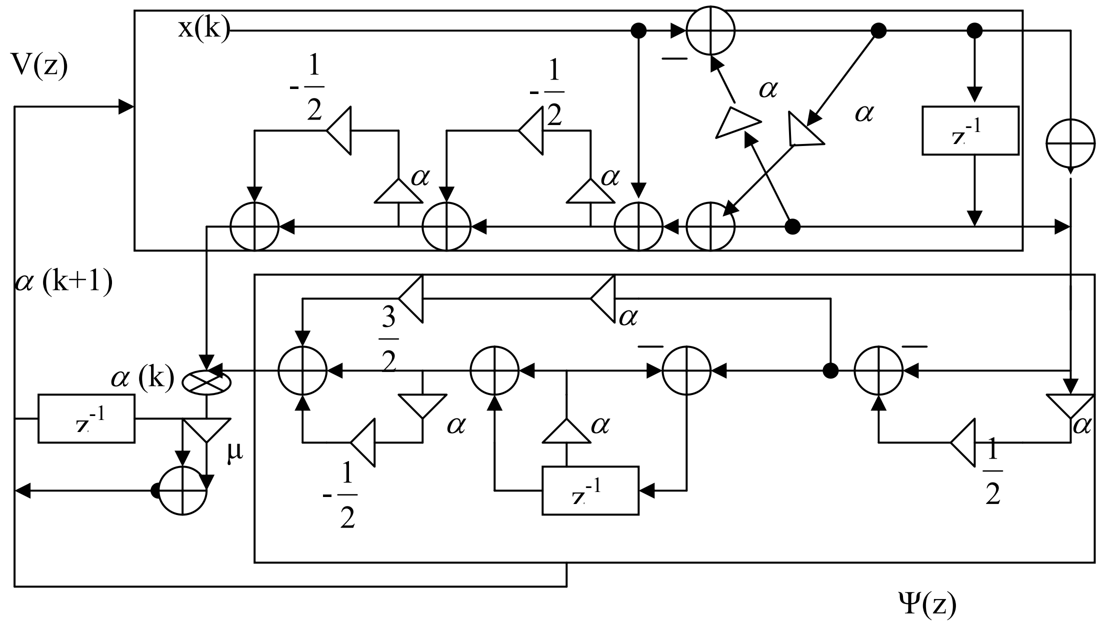

Fig 4.5 :Structure of the system to detect the passband-edge frequencies

Next, we define the following performance function in order to evaluate the quality factor of the detection of passband edge frequencies.

$$\upsilon = 1 - \frac{1}{\pi}\left|\omega_c - \Omega_c\right| \qquad (4.27)$$

4.4 THE HIGH PASS ADAPTIVE FIR FILTER

A high pass filter is a circuit that attenuates the low frequency signals from the input signal and allows the high frequency signal to go through it unattenuated.

A *finite impulse response* (FIR) filter is a filter structure that can be used to implement almost any sort of frequency response digitally. An FIR filter is usually implemented by using a series of delays, multipliers, and adders to create the filter's output.

Fig 4.4 shows the basic block diagram for an FIR filter of length *N*. The delays result in operating on prior input samples. The h_k values are the coefficients used for multiplication, so that the output at time *n* is the summation of all the delayed samples multiplied by the appropriate coefficients.

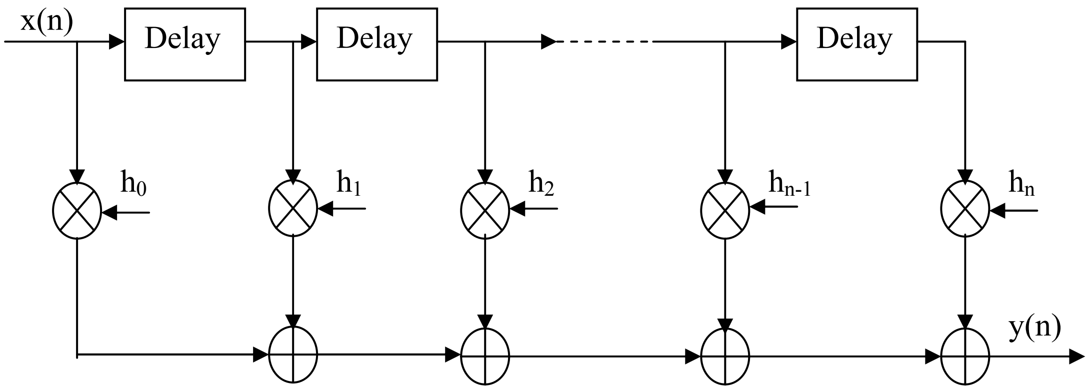

Figure 4.6 the basic block diagram for an FIR filter of length N

The system can be described by the difference equation as:

$$y(n) = \sum_{k=-\infty}^{\infty} h(k)x(n-k) \qquad (4.28)$$

or, equivalently, by the system function

$$H(z) = \sum_{k=0}^{M-1} b_k z^{-k} \qquad (4.29)$$

Furthermore the unit sample response of the FIR system is identical to the coefficients $\{b_k\}$, that is,

$$h(n) = \begin{cases} b_n, & 0 \leq n \leq M-1 \\ 0, & \end{cases} \qquad (4.30)$$

Digital filters with finite-duration impulse response (all-zero, or FIR filters) have both advantages and disadvantages compared to infinite-duration impulse response (IIR) filters. FIR filters have the following primary advantages:

- They can have exactly linear phase frequency response.
- They are always stable.
- The design methods are generally linear.
- They can be realized efficiently in hardware.
- The filter startup transients have finite duration.

The primary disadvantage of FIR filters is that they often require a much higher filter order than IIR filters to achieve a given level of performance. Correspondingly, the delay of these filters is often much greater than for an equal performance IIR filters.

4.4.1 Design Of Linear-Phase FIR Filters Using Windows Technique

For FIR filters, no design technique exist in the continuous time domain that could be used as a basis for the design of related digital filters as in the case of IIR filters. So, each filter design has to pass, in principle, a complete mathematical design procedure. The starting point of all the design algorithms is the assumption of idealized frequency response or tolerance specification in the passband and stopband. The finite length of the unit-sample response and hence the finite number of filter coefficients limits the degree of approximation to the given specification. Low variation of the magnitude (ripple) in the passband, high attenuation in the stopband and sharp cutoff are competing design parameters in this context.

In this method the *desired frequency response specification* $H_d(\omega)$ is given and the corresponding unit sample response $h_d(n)$ is determined. Indeed, $h_d(n)$ is related to $H_d(\omega)$ by the Fourier transform relation

$$H_d(\omega) = \sum_{n=0}^{\infty} h_d(n) e^{-j\omega n} \tag{4.31}$$

Where,

$$h_d(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} H_d(\omega) e^{j\omega} d\omega \qquad (4.32)$$

in general, the unit sample response $h_d(n)$ obtained from eq(4.32) is infinite in duration and must be truncated at some point, say at n = M-1, to yield an FIR filter of length M. truncation of $h_d(n)$ to a length M-1 is equivalent to multiplying $h_d(n)$ by a “rectangular window” defined as

$$W(n) = \begin{cases} 1, & n = 0,1,2,...,M-1 \\ 0, & otherwise \end{cases} \qquad (4.33)$$

Thus the unit sample response of the FIR filter becomes

$h(n) = h_d(n)*W(n)$

$$= \begin{cases} h_d(n), & n = 0,1,2,...,M-1 \\ 0, & otherwise \end{cases} \qquad (4.34)$$

The multiplication of the window function w(n) with $h_d(n)$ is equivalent to convolution of $H_d(\omega)$ with $W(\omega)$, where $W(\omega)$ is the frequency domain representation of the window function, that is

$$W(\omega) = \sum_{n=0}^{M-1} \omega(n) e^{-j\omega n} \qquad (4.35)$$

Thus, the convolution of $H_d(\omega)$ with $W(\omega)$ yields the frequency response of the (truncated) FIR filter. That is,

$$H(\omega) = \frac{1}{2\pi} \int_{-\pi}^{\pi} H_d(\upsilon) W(\omega - \upsilon) d\upsilon \qquad (4.36)$$

The window function has a magnitude response

$$|W(\omega)| = \frac{|\sin(\omega M/2)|}{|\sin(\omega/2)|} \qquad \pi \le \omega \le \pi \tag{4.37}$$

and a piecewise linear phase

$$\Theta(\omega) = \begin{cases} -\omega(\frac{M-1}{2}), & when \sin(\omega M/2) \ge 0 \\ -\omega(\frac{M-1}{2}) + \pi, & when \sin(\omega M/2) \prec 0 \end{cases} \tag{4.38}$$

Table 4.1 lists several window functions that possess desirable frequency response characteristics. All of the windows have significantly lower sidelobes compared with the rectangular window. These window functions provide more smoothing through the convolution operation in the frequency domain, and as a result, the transition region in the FIR filter response is wider. To reduce the width of this transition region, the length of the window is increased simply which results in a larger filter.

For the design of our High Pass Filter a “Blackman window” of length 55 is taken, as it gives considerably good attenuation at the stopband frequency and have a faster transition from passband to stopband.

TABLE 4.1 Window Functions for the Filter Design

Name Of Window	**Time domain Sequence** **h(n), 0≤ n ≤ M-1**
Blackman	$0.42 - 0.5\cos\left(2\pi\frac{k}{n-1}\right) + 0.08\cos\left(4\pi\frac{k}{n-1}\right)$
Hamming	$0.54 - 0.46\cos\left(2\pi\frac{k}{n-1}\right)$

Bartlett(triangular)	For n odd $\frac{2k}{n-1}, \quad 0 \le k \le \frac{n-1}{2}$ $2-\frac{2k}{n-1}, \quad \frac{n-1}{2} \le k \le n-1$ For n even $\frac{2k}{n-1}, \quad 0 \le k \le \frac{n}{2}-1$ $\frac{2(n-k-1)}{n-1}, \quad \frac{n}{2} \le k \le n-1$
Hanning	$0.5(1-\cos)\left(2\pi\frac{k}{n-1}\right)$
Kaiser	$\begin{cases} 0.1102(\alpha-8.7), & \alpha > 50 \\ 0.5842(\alpha-21)^{0.4} + 0.07886(\alpha-21), & 50 \ge \alpha \ge 21 \\ 0 & \alpha < 21 \end{cases}$
Bartlett-Hann	$0.62-0.48\left\|\left(\frac{k}{n-1}-0.5\right)\right\|+0.38\cos\left(2\pi\left(\frac{k}{n-1}-0.5\right)\right)$

The time domain and the frequency domain characteristics of the Blackman window with the window length 55 is shown below in Fig 4.5 and 4.6:

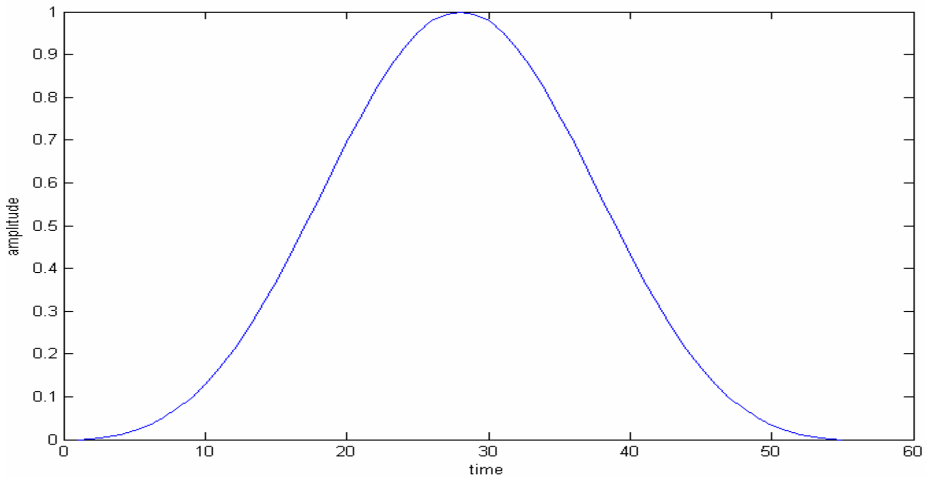

Figure 4.7 time domain characteristic of Blackman window

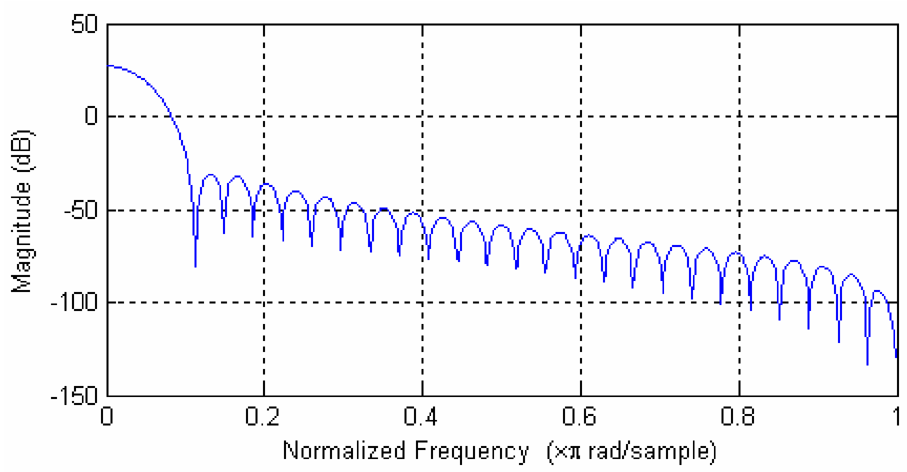

Figure 4.8 frequency domain characteristic of Blackman window

4.5 PREDICTIVE FILTER

A lattice predictor has a modular structure, in that it consists of a number of individual stages, each of which has the appearance of the lattice. It consists of M stages; the number M is referred to as the predictor order. The m^{th} stage of the lattice predictor is described by the pair of input-output relations

$$f_m(n) = f_{m-1}(n) + \kappa^*_m b_{m-1}(n-1) \qquad (4.39)$$

and

$b_m(n) = b_{m-1}(n-1) + \kappa_m f_{m-1}(n)$ (4.40)

where m= 1,2,…,M, and M is the final predictor order. The variable $f_m(n)$ is the m^{th} forward prediction error, and $b_m(n)$ is the m^{th} backward prediction error. The coefficient κ_m is called the m^{th} reflection coefficient. The forward prediction error $f_m(n)$ is defined as the difference between the input u(n) and it's one step predicted value; the latter is based on the set of m past inputs u(n-1),…,u(n-m). correspondingly the backward prediction error $b_m(n)$ is defined as the difference between the input u(n-m) and it's backward prediction based on the set of m future inputs, u(n),…,u(n-m+1).

The adaptive predictor filter here uses LMS algorithm to predict the value of input samples. The algorithm is defined as:

$y(n) = w^T(n-1)*u(n)$ (4.41)

$e(n) = d(n) – y(n)$ (4.42)

$w(n) = w(n-1) + f(u(n),e(n),\mu)$ (4.43)

The weight update function, for the LMS adaptive filter algorithm, is defined as

$f(u(n),e(n),\mu) = \mu*e(n)u^*(n)$ (4.44)

where,

n, The current time index

u(n), The vector of input samples at step n

u*(n) The complex conjugate of the vector of input samples at step n

w(n) The vector of filter weight estimates at step n

y(n) The filtered output at step n

e(n) The estimation error at step n

d(n) The desired response at step n

μ The adaptation step size

4.6 CONCLUSION

The modeling and designing of Synchronised Adaptive Filter is conceptualised here and the model is now constructed in the MATLAB Simulink environment for its verification and testing.

CHAPTER –V

SIMULATION OF PROPOSED FILTER SYSTEM

5.1 GENERAL

The model of the proposed filter is developed in the MATLAB Simulink environment Simulink platform offers modeling, simulation, and analysis of dynamic systems through dynamic processing. The Synchronous Adaptive Filter has been developed in the Simulink also using its Signal Processing Toolbox.

The block diagram of the composite SAF is shown below in fig5.1

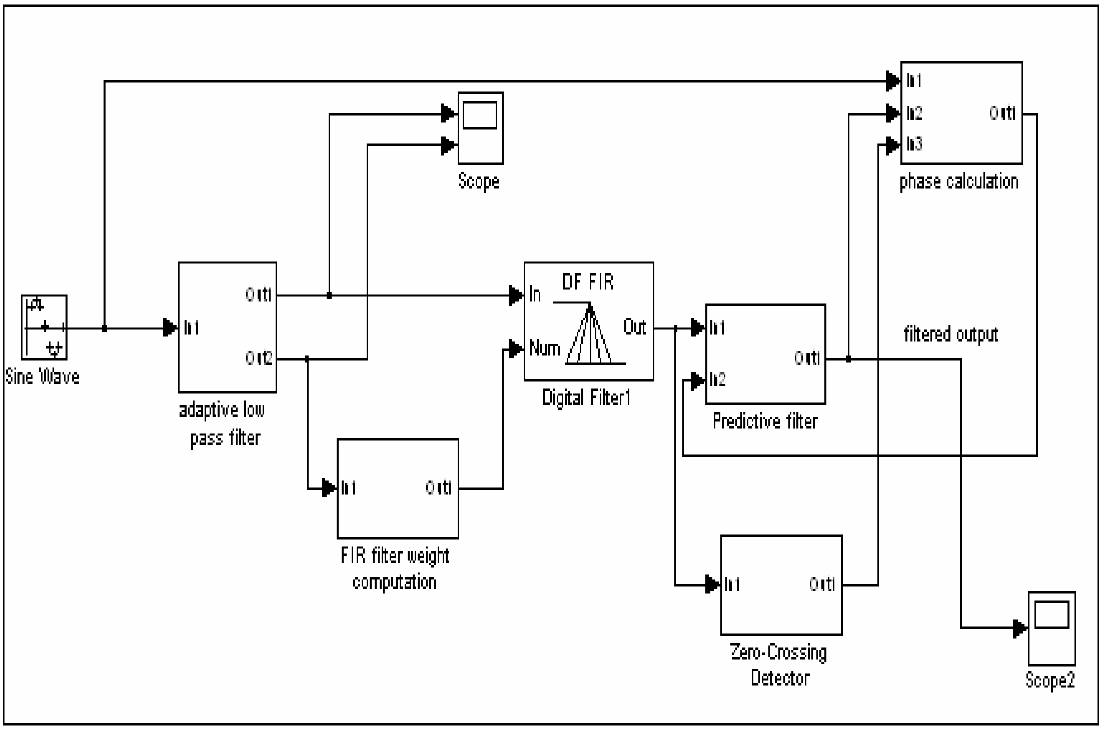

Figure 5.1 Block diagram of the Synchronised Adaptive Filter Developed in Simulink toolbox of MATLab

5.2 MATLAB BASED FILTER SYSTEM DEVELOPMENT

The Synchronous Adaptive Filter model is developed in three stages of Adaptive Low Pass Filter, Adaptive High Pass Filter and the Predictive Filter. With the simulation and verification of each stage done individually followed by testing of the integrated system.

5.2.1 Adaptive Low Pass Filter

The model of the developed low pass filter is shown below in fig.5.2

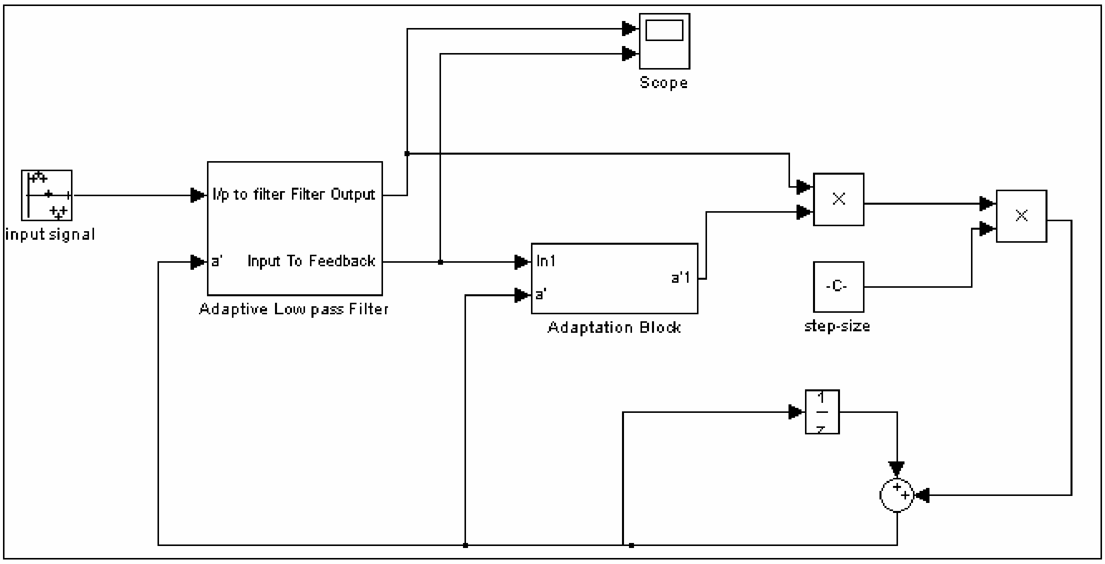

Figure 5.2 Block diagram of adaptive low pas filter

the test input signal is given by:

x= 2*sin(2*pi*50*n)+sin(2*pi*100*n)

The input signal along with the filtered output is shown below in Fig 5.3. it may be observed that the 100Hz signal is suppressed. The gain of ALF block needs to be adjusted if it is to be used alone. The adapted cross over frequency selected by adaptation block is 60 Hz.

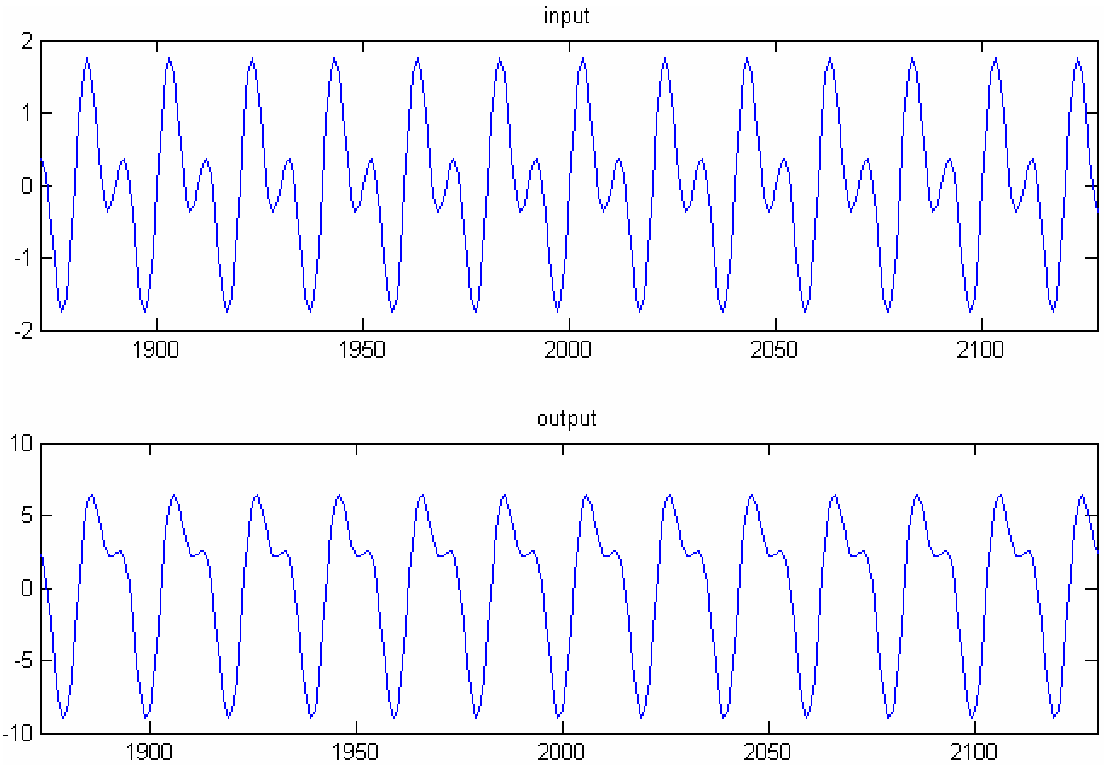

Figure 5.3 the input and output values of adaptive low pass filter

The variation of the adaptive filter variable for different input signal values is given in fig 5.4

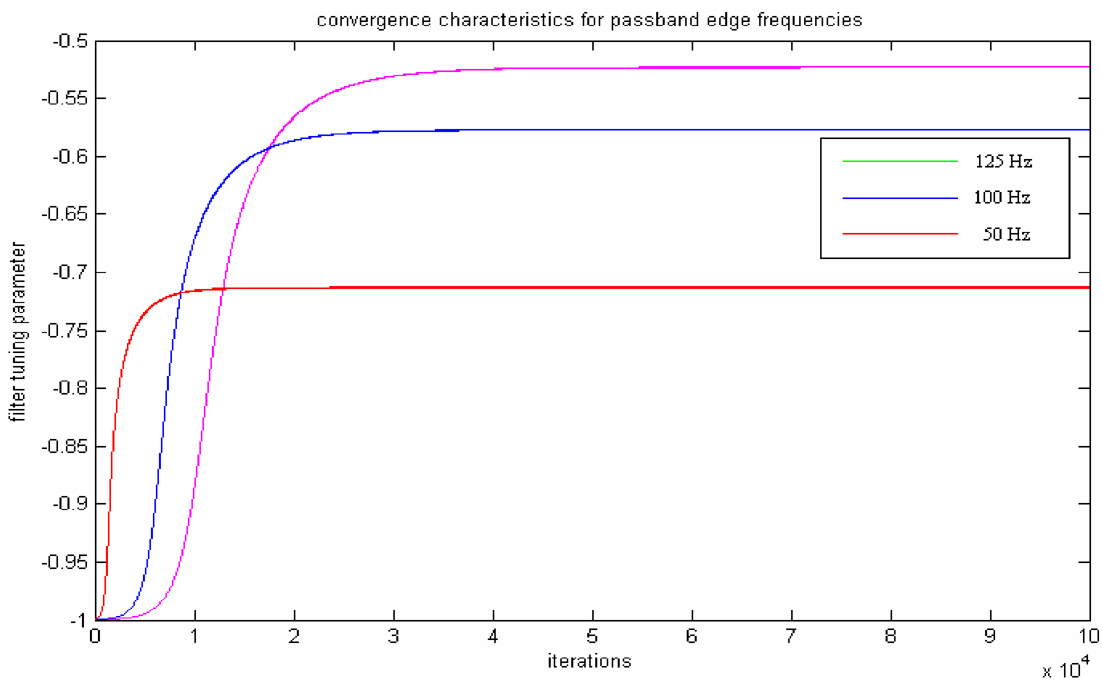

Figure 5.4the adaptive variable for different input signal

5.2.2 Adaptive High pass filter

The output of ALF is fed to the input of the adaptive high pass filter with adaption cross over frequency such that the band of 10 Hz is maintained.

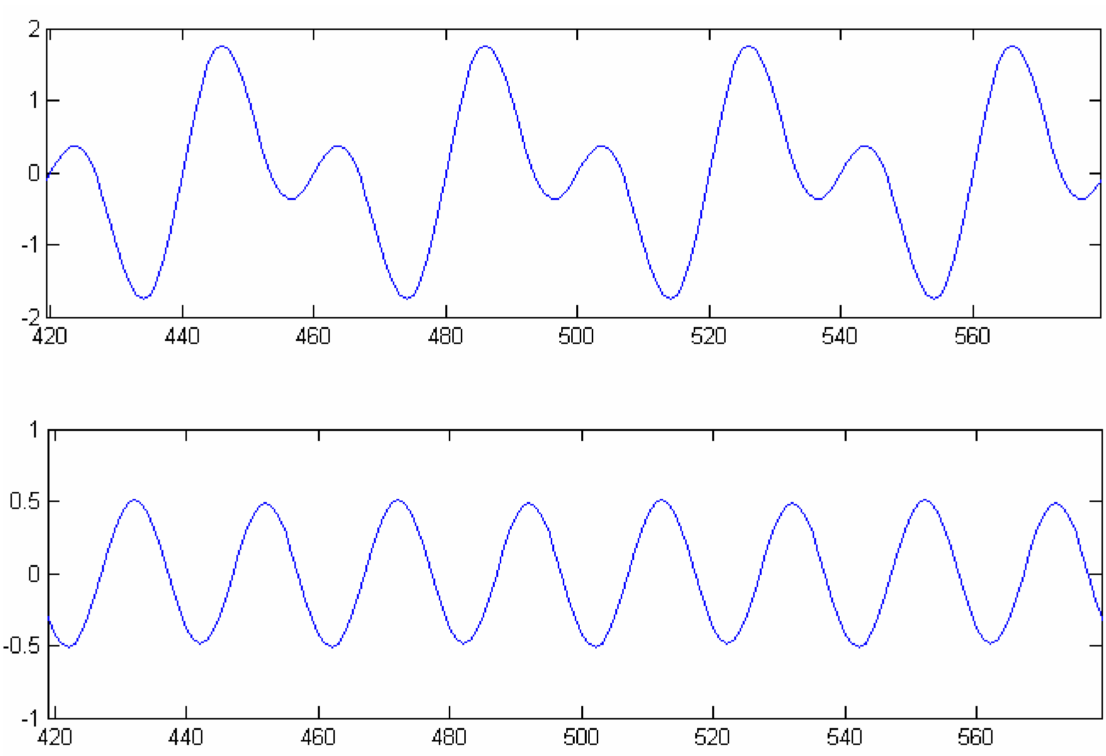

Figure 5.5 the input and output signals of the high pas filter

5.2.3 Predictive Filter

The received output from adaptive high pass filter is then fed to the predictive filter for phase compensation. The predictive filter is designed to act as one step ahead predictor, the input and output signal waveforms are shown in fig5.6-5.7.

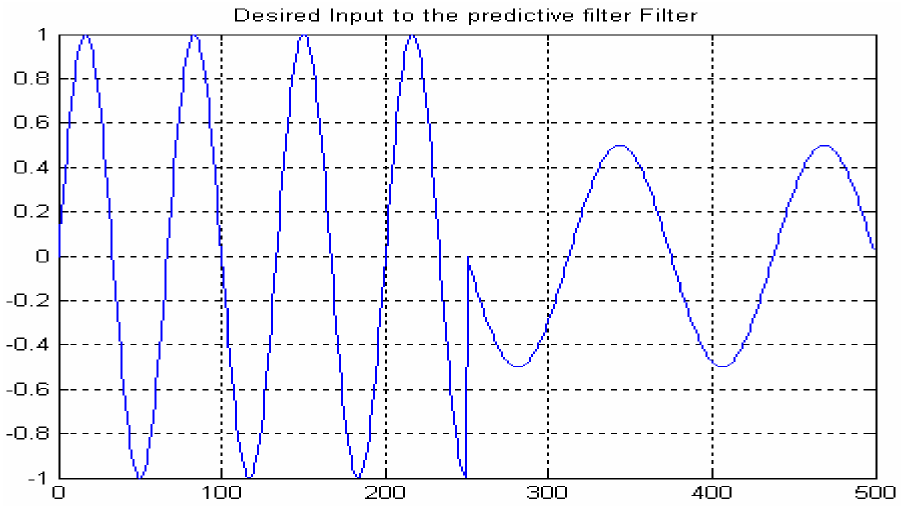

Figure 5.6 the input to the predictive filter

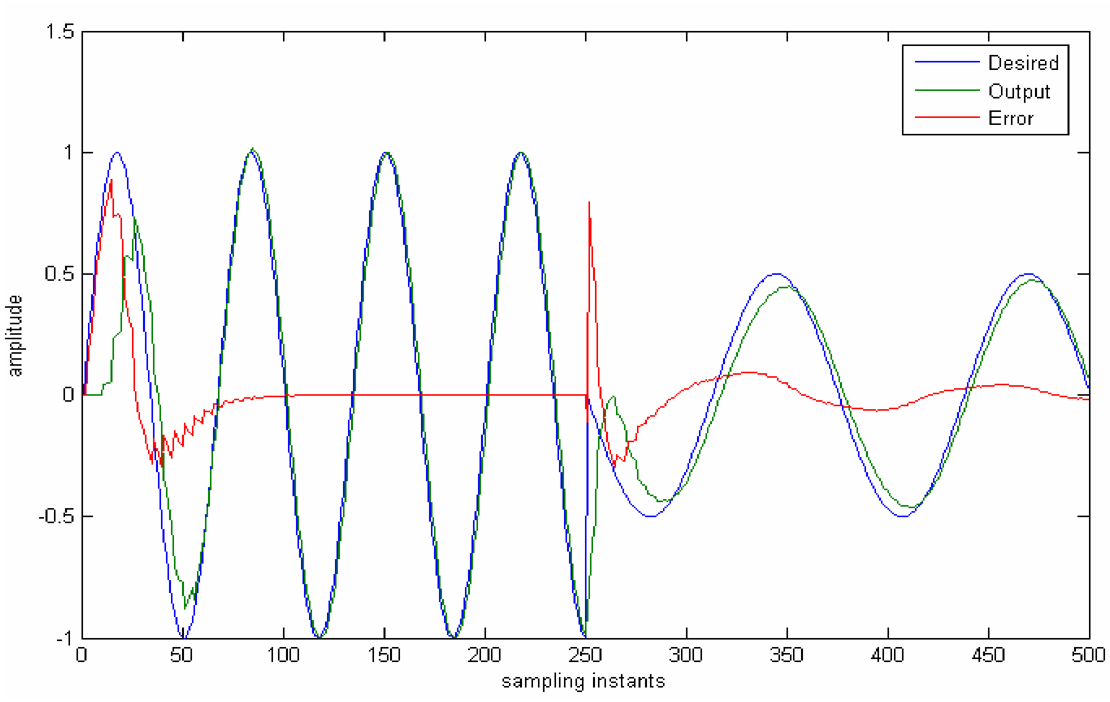

Figure 5.7 the output of the one step ahead predictor

The composite output of the filter for the input signal of

x = 0.5*sin(2*pi*0.150*n)+sin(2*pi*0.050*n)+0.4*sin(2*pi*0.025).

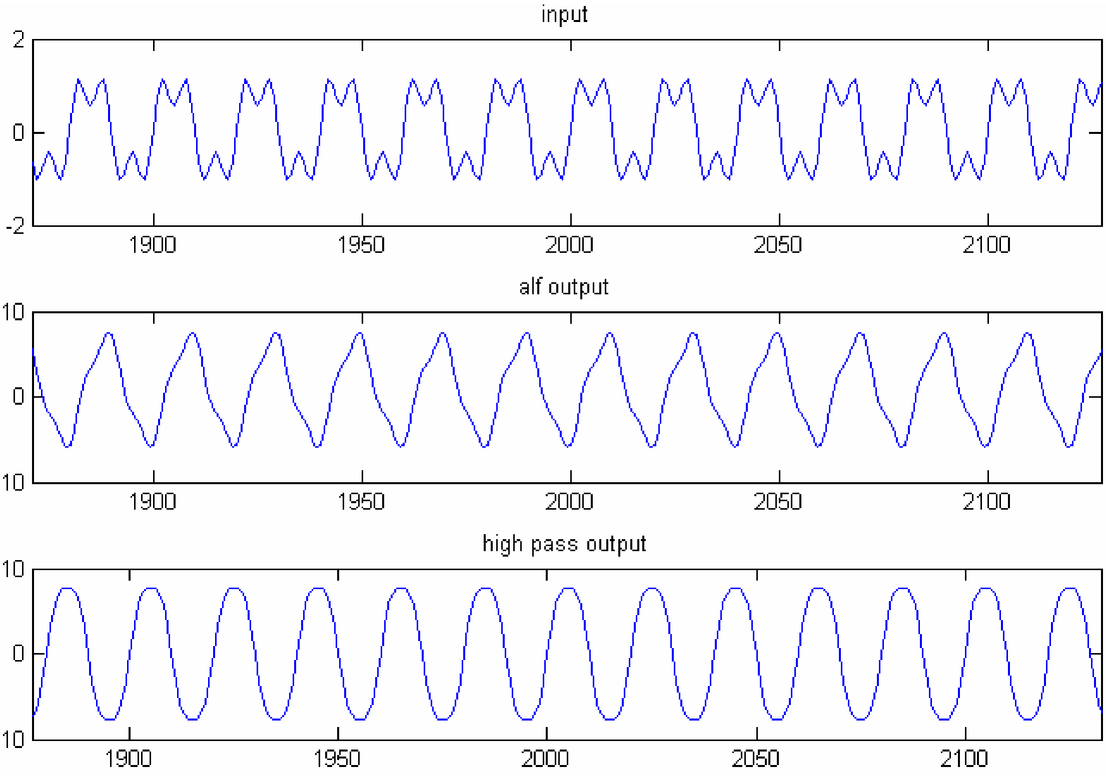

Figure5.8 the output of the ALF and high pass filter connected in tandem

5.3 CONCLUSION

- It may be observed that Alf, HPF and predictive filter have responded as per design specifications.
- MATLAB model developed have shown the adaptive characteristic of ALF for different frequency range.
- Predictive filter has compensated the phase error caused by previous stages of filtering.
- Overall system has successfully filtered all the distortions in the signal without any delay.

CHAPTER-VI

CONCLUSION AND FURTHER SCOPE OF WORK

6.1 MAIN CONCLUSION

The system designed here is dealt in three different modules consisting of an adaptive low pass filter, an adaptive high pass filter and a predictive filter stages in series to obtain the fundamental component of voltage or current signal from the power line.
The system is designed, tested and verified successfully under the MATLAB Simulink environment. The Simulation is done for each stage successfully and the results obtained are within the error limit. Thus the goal of the project listed below is achieved

- The proposed system should show satisfactory performance under steady state and the error should be within limits.
- The system should be able to reject both harmonics and subharmonics distortion for the voltage signal successfully.
- The system should be able to work under the noisy environment since adaptation is to be done dynamically for its operation.

6.2 FUTURE SCOPE AND WORK

Since the proposed SAF system is divided into three major modules and each being designed individually and then connected together this makes the model a bit complex and bulky. However, the analysis and design may be done considering all three aspects together; such attempt would reduce the complexity of this system for its implementation on Digital signal Processor.
The system may be implemented on DSP for experimental validation of simulated results.
Also, there is a scope of tuning adaptation of coefficients of the filter by application of fuzzy logic or neural network. The adaptive algorithm used for proposed filter system gives satisfactory response in steady state but lacks the fastness in tracking the changing signal. A new adapting tuning algorithm using fuzzy or neuro-fuzzy can be applied to the adaptive filter for tuning filter weights, that will not only optimizes the filter efficiency but also its tracking capability.
Finally the MATLAB model can be implemented on a DSP kit for its experimental validation.
The design may be optimized for enhancement of system efficiency.

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