ENHANCED ADAPTIVE SYSTEM FOR NOISE CONTROL

A THESIS

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DOCTOR OF PHILOSOPHY

by

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CERTIFICATE

I hereby certify that the work which is being presented in thesis entitled "***Enhanced Adaptive System for Noise Control***" submitted to the Department of Electrical and Instrumentation Engineering, Thapar Institute of Engineering and Technology (Deemed to be University), Patiala in the fulfilment of the requirements for the award of degree of **"Doctor of Philosophy"** is an authentic record of my own research work carried out under the guidance of **Dr. Smarajit Ghosh** and refers other research work, which are duly listed in the reference section.

The matter presented in this thesis has not been submitted in part or full for the award of any degree in any other University or Institute.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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Dedicated

to my

Father Shri Jal Singh Walia

and

Mother Smt. Deepak Walia

ABSTRACT

The source of noise is becoming the important criteria as the environment is affected due to the high reflection of the sound waves. A few algorithms are introduced in this thesis, which can be used to cancel the noise from the environment. The new ANC system is built with a modified FsLMS (MFsLMS) algorithm and along with a PSO-FF hybrid algorithm has been compared with a FLANN-FIR hybrid filter along with FF algorithm and FsLMS algorithm. Nonlinear noise cancellation has been depicted in this dissertation. The developed ANC systems are studied in the presence of different noise signals like Gaussian and Chaotic noise. Simulation results are provided and the performance of each technique under various circumstances are compared with the existing techniques. A modified FsLMS (MFsLMS) algorithm is proposed with a hybrid PSO-FF optimization technique. The hybrid optimization is used to find the stability factor of the system. The proposed method can upgrade the stability of the ANC system. The modification of the existing algorithm is done with Maclaurin series. With this modified method, computing time and complexity can be reduced by comparison with existing methods. Existing methods are used to compare simulation results. The comparison shows that the proposed method has a lower computing complexity compared to the other existing methods. The analysis of the proposed method is performed with two noise signals. Chaotic noise and Gaussian noise signals are chosen. A hybrid combination of functional link artificial neural network and finite impulse response (FLANN-FIR) filter is used with ANC system. In the proposed method, filter coefficients are evaluated through the firefly optimization algorithm. Normalized mean square error (NMSE) value is evaluated through the FsLMS algorithm. The convergence of the system has been enhanced through specific methods. The error value is inversely proportional to the convergence of the system. When the value of the error is reduced, the convergence value has been increased. The simulation results show better convergence of the system. Simulation is carried with same noise signals of Chaotic and Gaussian noises. The proposed method is also compared with the BAT algorithm in which the FF algorithm is replaced by the BAT algorithm. From the simulation results denoised signals are obtained after the implementation of the two methods. The computational complexity has been considerably reduced in comparison with the BAT algorithm.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATION

Serial No.	ABBREVIATION	
1	ANC	Active noise control
2	DSP	Digital signal processing
3	LMS	Least mean square algorithm
4	FsLMS	Filtered-s least mean square algorithm
5	FxLMS	Filtered-x least mean square algorithm
6	MFsLMS	Modified filtered-s least mean square
7	HPSOFF	Hybrid particle swarm optimization firefly algorithm
8	PSO	Particle swarm optimization
7	FFA	Firefly algorithm
8	NMSE	Normalized mean square error
8	FLANN	Functional link artificial neural network
9	FIR	Finite impulse response
10	IIR	Infinite impulse response
11	ANN	Artificial neural network

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Active Noise Control (ANC) is an approach, which has been used to reduce noise in any source signal. The environment contains undesirable noises, which may interfere with the needed signal and reduces its lucidity. Specific noise control is generally connected in the field of acoustics. The idea behind ANC is that it can create optional waves from another source using filters. In ANC system, the signal has the same amplitude of the actual one, but anti-phase. Unwanted signals can therefore be removed. The improved techniques have been developed for noise suppression since 1990. The strategies are presented here as the expansion of noise level by means of motors, blowers, fans and so on. This system can effectively reduce low frequency noise, and the ANC controller can generate the control signal at the secondary lateral source, in which the digital filter can act as an ANC controller. This system is to be typically active and passive noise controller. The way of reducing the sound in active and passive controllers is the power source, and isolating materials, respectively. Active noise cancellation is only suitable for low frequencies, and the passive noise controller is suitable for the converse process. The illustration of the ANC structure is shown in Fig. 1.1. The feed-forward ANC system is normally in use. This includes a reference microphone and an error microphone. The presence of noise is to be supervised through the reference microphone. The error microphone should be considered as the residual noise, and the loudspeaker can cancel the sound. The controlling measures are the,

- Coherence
- Active vibration control
- Noise control
- Noise-cancelling headphone, and microphone

The noise sources are classified as,

- Electronic noise
- Electromagnetic noise
- Acoustic noise

- Electrostatic noise
- Quantization noise

The applications of ANC are still having certain limitations owing to its effectiveness of the signal processing algorithm, economic barrier, and other constraints. The potential benefits of the ANC system arise due to its installation, which is given below.

- Non-obtrusiveness
- Retrofitting
- Convenience

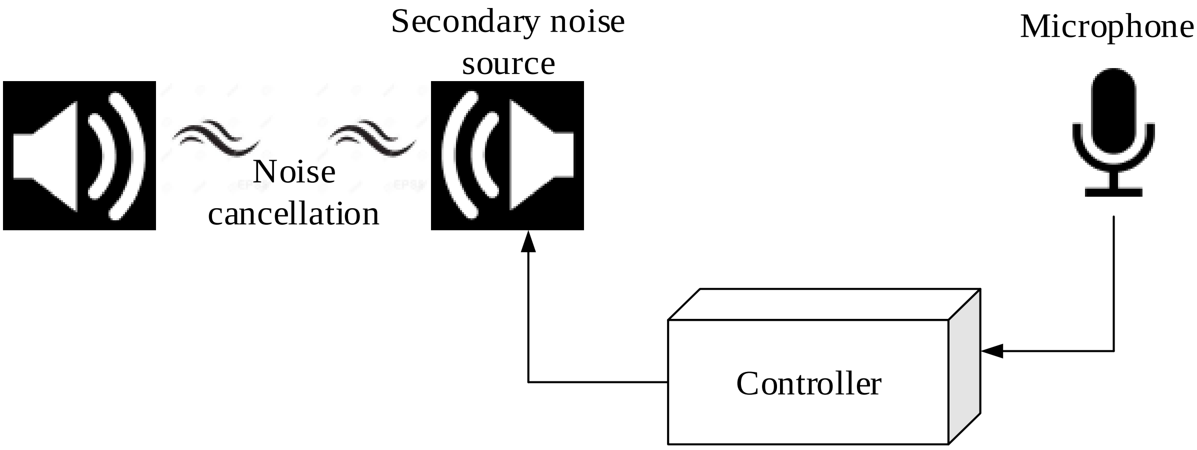


Figure 1.1: Illustration of active noise control

1.2 TYPES OF NOISE

Numerous varieties of noise have been targeted by different ANC schemes with varying levels of accomplishment.

a). Single Frequency: It is a simple noise. For the main components of noise reduction, this is not practical. The noise signal is analyzed that make it feasible to speculate about the techniques used in real-world active noise cancellation. The ANC system cancel out the noise signal.

b). Periodic: The ANC has been particularly effective in quasi-periodic signals with the periodic noise, and these signals are repeated occasionally. Pure periodic signal occurs and provides basic patterns of quasiperidic signals. These quasiperide signals are considered as periodic signals with additive noise. An engine exhaust noise is an example of a quasi-periodic signal. At the firing of each cylinder, the noise signal is produced, and it does not vary between periods.

c). Narrow Band: This type of noise collects the narrow range of frequencies, and these frequencies are very critical to be removed with the ANC. However, this frequency is not complex for broad band noise. In the narrow band frequency, the ANC can be specifically efficient.

d). Broadband: The broadband frequency gives more critical ANC issues. This becomes more problematic when compared to other types of frequency. It is very complex when the noise prediction is performed at any position. The problem can occur if the signal contains noise, which is to eradicate the noise without cancelling the signal. For broadband signals, the approaches of the ANC are essentially arithmetical in the environment.

1.3 PRINCIPLES

Noise is a significant crisis experienced by human beings. The elevated level of exposure will result in many serious health problems associated with mental loss or even permanent or temporary hearing loss. Acoustic, therefore, has a special importance in this scenario. Because of the enormous surge in technology, environmental noise disturbance is increasing. Enormous instruments are used in the industrial field as pumps and big machines, which play the major role in this high noise situation. Noise is also an agent of pollution that can have many harmful effects on nature. Humans are also the victims of pollution through terrible illnesses such as fatigue, blood pressure imbalance, stress, etc.

Many kinds of research have been carried out to alleviate noise problems. Companies are given a strict noise limit even though some large machines need to work. As a result, adequate monitoring procedures were required to address this problem. From the start, numerous conventional methods are available. Enclosures, barriers, and silencers are a few of them being used. They follow the simple concept to the point. Captivating sound materials make a vital contribution. These substances will soak up the noise. The methods mentioned do not apply to low-frequency noises. ANC is a solution to the issue, which is an amended regulation developed by electro-acoustic. Low-frequency wave forms have a higher wavelength. The proposed control can manage such disturbances. The operating principle is that there will be two sources called primary and secondary for generating waves, which have the same amplitude and out of phase interfered with each other. Commonly, loudspeaker or compressed air flow is adopted as secondary sources. Electrical signals control the acoustic output of these devices.

The basic standard for active sound attenuation is the critical intrusion of two distinct sound waveforms by generating appropriate interfering signal at an appropriate time and an appropriate location. But the understanding of the ANC system is problematic. The following principles are simple to the active noise abatement area.

a). Young's Principle: It is the foundation of the ANC, which states that the pressure wave propagation can cancel the addition of the inverted waveform in space. This effect is replicated for a simple tone. The inversion is just an 180^0 phase shift for simple tones. The principle coordinated precisely at every point along its path to annul a waveform efficiently. In this principle, the sound waves have individual radiation, and an exact match is almost difficult to make out.

b). Huygen's principle: This principle is similar to a Young principle procedure, but it provides a technique for reducing wide-area noise. It considers a field that is entirely divided by a closed surface from a set of sound resources.

1.4 SUMMARY

This chapter describes the Active noise control (ANC) system approach, type of noises in terms of ANC schemes. It also outlines the basic principles related to active noise reduction (ANR). The literature review of the ANC has been presented in Chapter 2. The details of the ANC and the existing algorithms of the ANC have been discussed in Chapter 3.

CHAPTER 2

LITERATURE SURVEY

A study of the literature on the ANC system shows progress in the following areas.

2.1. Literature Review

ANC is a standout amongst the most prevalent applications of adaptive filters. The expanding fields of application of signal processing are ANC. The fundamental concept for active control of acoustic noise is to infuse an auxiliary sound drop of the essential sound utilizing destructive interference. Along these lines, it is a technique to cancel the noise from the noisy signal. This method can reduce undesirable sound by the inclusion of a specifically designed second sound to cancel the first one. Machines can truly be an aggravation with their burst of huge disturbances; our fragile ears fall prey to the noisy climate of their being. With the expansion in the quantity of mechanical hardware, the issue has turned out to be increasingly apparent. Passive silencers are esteemed for their excessive attenuation over a wide. They are moderately expensive, large and unable at low frequencies. Ongoing years the ANC has been picked up very fame to the commotion, and to make less loud conditions for work. Utilizing essential standards of wave superposition and wave abrogation, the ANC has confronted various viable issues. Many devices are using ANC to reduce the unwanted noise from the signal to improve the quality of sound.

Angevine ***et al.*** (1980) submitted a methodology wherein the secondary sources on the surface of a Huygen performed as an absorber of sound, and the field of the sound might terminate entirely exterior to the surface of the Huygen. Hence the upsurge in radiation exterior to the horizontal angle was also decreased since termination was over a constricted range.

Morgan (1980) discussed a comprehensive study on an approach, namely the LMS algorithm or multiple correlation cancellation loops during the occurrence of a linear filter in the path of an auxiliary signal. Solutions to this problem, along with numerous examples of signals, were also presented. Although, he only discussed examples of simple signals, which was the primary disadvantage of his method.

Roure (1985) emphasized a network modelled for industrial applications, which were the self-adaptive type of programmable digital filter. Here, he described the concept behind an ANC network in an air conditioning duct. Because of the auto-adaptive nature of the system, it could be injected on-site as a silencer.

Eghtesadi ***et al.*** (1986) proposed an ANC with dual concepts causing the deprivation of performance via utilizing the regulatory techniques, and hence a nonlinear controller had been executed. Simulations were performed and derivations associated with non-linear and linear system controllers were presented.

Elliot ***et al.*** (1987) presented an algorithm for adjusting the array coefficients of FIR filters and the throughputs obtained were associated linearly with other arrays of error revealing points to reduce the sum of MSE signals. The applications regarding algorithm were also discussed. The main application of that algorithm was in the field of ANC at a unique frequency.

Eriksson ***et al.*** (1987) mentioned the utilization of adaptive filters for the termination of noises and illustrated that IIR filters had numerous features to resolve the dispute. The recursive least mean square algorithm was employed in that methodology wherein the encompassed noticeable benefits for the utilization of the practical termination network.

Nelson ***et al.*** (1987) suggested an optimization methodology that used an explicit quantification of the power output of the sound. In their method the noisy signal had been purified by inserting secondary sources. Considering the number of secondary sources, it was possible to achieve the decrease in total output power when it was separated from the primary sources.

Elliot ***et al.*** (1988) established an ANC method to overcome the conventional methodologies for reducing the undesirable noises. The proposed methodology focused on cancelling the low-frequency noise signal.

Eghtesadi and Gardner (1989) proposed an innovative algorithm called the RLMS algorithm that overcame the limitations of LMS and other similar algorithms. The algorithm could be called filtered U algorithm due to operating alternative path transfer functions.

Fuller ***et al.*** (1989) described dual configurations of ANC utilizing FF methodology. The anticipated ANC was based on FxLMS algorithm. Numerous investigations were performed to estimate the anticipated methodology for decreasing the noise at the blade passing frequency by exploiting FF adaptive regulation.

Ueda and Suzuki (1990) enhanced the transmission boosts by the functioning of high bit-rate digital mobile radio communication in frequency-selective blurring environments. For that purpose, a retraining recursive least squares (RT-RLS) computation for a decision feedback equalizer (DFE) was proposed. Assessment tests were done with a real-time trial condition that incorporated a DFE actualized by a single chip digital signal processor (DSP). Examinations were performed by transmitting 250 kB/s quadrature phase-shift keying (QPSK) at a most extreme Doppler frequency up to 160 Hz. The test calls for a two-wave demonstration, in which the waves had similar power and varied freely with the Rayleigh distribution.

Nishimura (1991) suggested an innovative technique for designing an online path of secondary in ANC networks, which utilized only two filters like modified FxLMS algorithm along with variable step-size LMS. Initially, a varying step was used in LMS algorithm, to improve its performance so that the performance of ANC systems would be enhanced.

Elliott and Nelson (1993) stressed the importance of achieving clarity in the ideologies of electrical control as well as on acoustics to fulfill an obligation on the advantages and inadequacies of the ANC system. The approaches for electrical control, along with the applications of ANCs, were also discussed. However, the methodologies described may not be suitable for practical applications, which was the main flaw in their method.

Kuo and Luan (1993) developed an innovative ANC algorithm that uses two interactive FxLMS adaptive filters to reduce noise, consequently design the online error path. The rate of convergence of the anticipated algorithm established a lattice network for decorrelating the input of the reference. Additionally, the rate of convergence became faster with the lattice network owing to the impact of the adaptive lattice predictor.

Chang et al. (1994) presented an ANC system based on time-delay neural network. The objective of study was to design the noise cancellation method using a combination of loudspeaker and a transmission channel. The feed-forward neural network used in the study contained the ability to investigate nonlinearity and removal of noise.

Matsuura ***et al.*** (1995) established applications regarding an ANC network, and the main objective of their method was to guess the time-series information of the noise. When implementing the predictor in the ANC network, there was an improvement in the performance of an ANC, and it was therefore practical in a neural system.

Snyder and Tanaka (1995) established an adaptive algorithm permitting the consistent adaption of the controller contributing the capability to sustain causality in the regulation strategy. The results showed that the expected algorithm performed as a nonlinear as well as a linear controller, but the stability and predictability were comparatively low.

Kuo ***et al.*** (1997) investigated a frequency domain periodic ANC network, and the execution of the network is performed by LMS algorithm. To terminate noises in the narrowband, the synchronously sampled adaptive network for frequency domain performs as a comb filter. The simulation results validated the practical use of the expected approach, as well as the active noise equalization method. The noise spectrum for residual noise could be designed by controlling the gain constraints at a specific frequency tray.

Strauch and Mulgrew (1998) investigated dual concepts in ANC, causing the deprivation in performance using traditional linear control methodologies. In their concept, the first one was referred to as the noise, whereas the second one was specified that the ANC actuator network encompassed non-minimum phase. The algorithm utilized by them was the reconfigured FxLMS algorithm since standard one could not be utilized for nonlinear networks.

Bouchard ***et al.*** (1999) developed an algorithm for the control, and the aim is to produce more novel algorithms with an increased rate of convergence with a decline in the intricacy for computation. The approach gave an ANC with linear and nonlinear regulators with a nonlinear actuator.

Kuo and Morgan (1999) emphasized the fundamental algorithms for ANC regarding DSP execution, and the investigation was based on single-channel broadband control. However, the single-channel was advanced to multichannel in numerous situations. The applications of the anticipated approach to real-time problems were also examined.

Patra ***et al.*** (1999) proposed a FLANN algorithm, which encompassed the nonlinearity by the advancement of the source via polynomials of trigonometry. The comparative analysis of the performance of the FLANN with other algorithms showed better performance than other algorithms.

Lee ***et al.*** (2000) introduced an ANC network based on the lattice structure based filter in order to regulate the exhaust noise of the car. The anticipated methodology could be executed by exploiting a DSP and smeared to the exhaust noise of the engine to show its effective regulation.

Martins (2000) focused on an innovative methodology entitled as a fast multi-band ANC (FMB-ANC), which was based on the principle of multi-band ANC. The proposed methodology reduced crosstalk and instability. On the other hand, it improved the rate of convergence. A comparison of existing methodologies with the proposed methodology had shown that it outperformed all other approaches.

Qin and Hansen (2000) looked into the FxLMS algorithm. They introduced a modified algorithm for active control of periodic noise using the FxLMS algorithm, which utilized arbitrary noise for on-line cancellation of path transfer function (CPTF) estimation. Two short versatile channels were presented. One was an adaptive noise cancelling filter, used to improve the convergence speed of the CPTF demonstrating the filter in view of critical noise of enormous magnitude by dropping the segment of the error signal that was related to the primary noise. The other was an adaptive estimator, which was utilized to re-gauge the CPTF (long FIR filter assessed by random noise) with a short FIR filter by utilizing the intermittent reference signal as the input. The customary FxLMS algorithm was then utilized with the compressed FIR filter to filter out the reference signal. The primary path transfer function changed significantly quicker than the CPTF when noteworthy processing adaptability in factual circumstances had been given. The simulation results showed the adequacy of the proposed algorithm.

Geem ***et al.*** (2001) suggested a novel algorithm called harmony search algorithm (HAS) imitating the music players to overcome the shortcomings of the conventional algorithms. Travelling salesman problem estimated the performance of the anticipated algorithm.

Park ***et al.*** (2001) introduced an effective noise regularization algorithm based on the adaptive filter of delay less subband, and there would be a decline in the intricacy of computation of the subband. By utilizing a filter for small impulse response, a clarified reference signal was produced. A frequency-domain execution of the anticipated algorithm additionally set up the intricacy in the computation were also decreased.

Tan and Jiang (2001) presented a Volterra filtered-X least mean square (VFxLMS) algorithm based on a multichannel implementation for the feedforward ANC. The newly developed algorithm achieved performance improvement over the standard FxLMS algorithm when the secondary path estimated nonminimum phase and the reference nonlinear noise process at the same time.

Bouchard (2003) defined fast affine and multichannel affine projection algorithms for ANC, which aimed at terminating the noise signal. However, it could cause the formation of diverse structures that was a major concern. However, the computational intricacy was reduced along with an upsurge of the performance of convergence.

Sakai and Miyagi (2003) described an immobile point that was attained by utilizing the FxLMS algorithm by an associated methodology using a frequency domain approach. Later, a local convergence domain was established. Lastly, the condition of local convergence had been achieved and its validity had been demonstrated by numerous simulations.

Tahir ***et al.*** (2003) suggested an ANC algorithm based on adaptive filtering with averaging (AFA), which had an analogous structure of FxLMS and hence named as FxAFA. The anticipated algorithm utilized the data averages to obtain the tap weight values of the ANC controller, and the outcomes showed a reduction in the computational intricacy.

In several applications, the acoustic noise created from active frameworks was nonlinear and deterministic or stochastic, non-Gaussian, and hued. Das and Panda (2004) explained that the linear strategies used to control the noise showed debasement in execution. The actuators of an ANC framework, all the time had a non-minimum-phase response. A linear controller under such circumstances could not demonstrate the inverse of the actuator and henceforth yielded poor execution. A new FsLMS-based ANC structure, which operated as a non-linear controller, had been proposed. The quick usage plan of the FsLMS method also granted. Results showed that the given methodology provided better outcomes than the FxLMS algorithm and even performed superior to that of the VFxLMS algorithm, as far as MSE, for controlling of nonlinear noise forms.

Shin ***et al.*** (2004) anticipated two innovative step-size algorithms on behalf of regularized LMS as well as affine projection. The projected methodology could produce an impact of a faster convergence rate and a decrease in the adjustment default error.

Kuo and Wu (2005) presented the FxLMS bilinear algorithm for nonlinear adaptive filters to address non-linear distortion and signal saturation problems that occured in ANC systems used for sustainable implementation. The performance of the adaptive filter was evaluated in terms of residual noise in the steady state, speed of convergence and computer complexity.

Das ***et al.*** (2006) introduced an innovative algorithm, namely FsLMS instead of numerous channel control of nonlinear noise practices. The intended approach reduced the complexity of the noise signals, which was better than other similar approaches. The main advantage was that the number of steps for the computation was also low.

Sciuranza and Carini (2006) presented an adaptive feedback ANC (AFANC) network for communication along with audio applications. Numerous considerations were taken for the modelling and execution of an ANC. Moreover, numerous innovative advancements to the anticipated network were also examined.

Sciuranza and Carini (2006a) discussed an effective network for nonlinear ANC, and it explained that simplified piecewise-linear extensions could efficiently substitute orthogonal and trigonometric extension of polynomials. The anticipated network was amended by exploiting an expansion of projection of affine algorithm.

A convex blend of adaptive filters was used by Zhang and Chambers (2006) to enhance the execution of a variable tap-length LMS plan in a low signal-to-noise condition (SNR 0 dB). As appeared by reenactments, the adjustment of the tap-length in the variable tap-length LMS computation was influenced by the parameter decision and the commotion level. Mix methodologies could enhance such adjustment by abusing points of interest of parallel adaptive filters with various parameters. They found better outcomes.

Riyanto (2007) introduced ANC for broadband noise, with the algorithm used in his methodology being the LMS algorithm. The broadband noise was considered within the duct along with the open space. The experiments were carried out using the attenuation level for a wide variety of locations.

Yucelen and Pourboghrat (2007) hosted an identification of the network by a recursive Kalman filter (RKF) evaluation methodology along with a vigorous control approach. They examined experimentally as well as theoretically for the ANC. The methodology aided in diminishing noise in a broad area of bandwidth, which was necessary for the field of the ANC. Real experiments in hardware utilizing DSP were performed for validating the applicability and the characteristics of the anticipated methodology.

Zhou and DeBrunner (2007) examined filtered error-based algorithms to resolve linear secondary trajectory problems and therefore, they expanded the expected algorithm. The algorithm was effective in computationally and retained a simple network. The computational intricacy could be reduced.

Gholami-Boroujeny and Eshghi (2008) proposed an innovative design to execute the on-line secondary track design of the ANC networks, and the four modules included in the design reduced unwanted noise. The algorithm used in this methodology was the FxLMS algorithm to assemble the weight of the tap. The outcomes of the execution provided rapid design and convergence.

Reddy ***et al.*** (2008) considered an effort to describe the execution of two non-linear ANCs, namely VFxLMS and FsLMS algorithms. The principle of reusing a portion of the computations done for the initial stage was utilized to execute the anticipated algorithms, which were effective in computation. Finally, the outputs were compared with that of the original ones.

Wu ***et al.*** (2008) established an effective ANC algorithm based on the adaptive filter for delay less subband and hence the intricacy in computation was decreased by exploiting a filter. For designing the path of the secondary transfer function in a condensed form and overlap save execution of the algorithm had been deliberated, and the outcomes illustrated that the characteristics had been improved.

Davari and Hassanpur (2009) established an innovative methodology for designing a secondary path in ANC networks. The secondary path was in line with the expected methodology. The anticipated algorithm was terminated at an optimal point to enhance the performance. The results of the simulations demonstrated that the proposed methodology was efficient.

Yang (2009) developed an innovative algorithm known as firefly (FF) for multimodal optimisation applications. The anticipated algorithm was in comparison with other analogous algorithms such as PSO. The results represented that the proposed algorithm was superior to other dominant algorithms.

Yang (2010) proposed BAT algorithm based on the behaviour of locating the echo, which was an innovative algorithm. The benefits of the prevailing algorithm were associated with the anticipated algorithm, and the outcomes of simulation demonstrated that the anticipated algorithm was supreme to other similar algorithms.

Zhao ***et al.*** (2010) proposed two innovative approaches based on functional link neural network (FLNN) for nonlinear ANC (NANC) networks having minimum intricacy in computation. To control the anticipated filter, a decline in the intricacy FsLMS algorithm utilizing the bank methodology had been implemented. It outperformed all other analogous methodologies and was efficient in diminishing the nonlinear impacts in NANC networks.

Alavi and Gandomi (2011) presented linear genetic programming as well as multi-expression programming by implementing the computation of numerous intricate problems. In contrast to the ANC, the anticipated approach encompassed prediction equations. The time consumption of the methodology was also quite low compared with other approaches.

Chen ***et al.*** (2011) illustrated an ANC utilizing unidirectional secondary sources, which encompassed of dual adjacently adapted phase difference. The secondary noise areas were accustomed in such a manner that it should be equal to the primary sound field. With the substitution of unidirectional sources in place of monopoles, there was an enhancement in the performance of the ANC.

Chaudhury ***et al.*** (2011) proposed a soft computing method to study the growing ANN.
Reddy ***et al.*** (2011) introduced a hybrid adaptive algorithm for an ANC network, which influenced the consistency of FxLMS algorithm utilizing the large convergence speed of Filtered x recursive mean squares (FxRMS) algorithm and the disputes inspired the algorithm in executing an ANC network. Reduced residual error along with a decline in the entire intricacy in the computation was the benefits of the hosted algorithm.

Sciuranza and Carini (2011) introduced a modified evolution of the famous trigonometric evaluations of FLANN filters to include the appropriate components of the input samples using different time lags (cross-terms). The outcomes deliberated that the FLANN filter using that methodology could be compared to Volterra filters with the reduction in intricacy.

Yang ***et al.*** (2011) utilized an association of an accelerated PSO along with a nonlinear support vector apparatus for making a network to resolve optimization problems regarding business. The initial phase was the employment of the algorithm in production optimization and successively utilized it for predicting the income.

Bismor (2012) defined the features of the LMS algorithm. Initially, it demonstrated novel essential conditions for the convergence of the predicted algorithm. The anticipated algorithm utilized by that approach was efficient and covered ANC and adaptive line advancement, which were the dual applications possible.

Carini and Sciuranza (2012) defined a new classification of FLANN filters referred to as complete FLANN (CFLANN) as well as it gratifies stone-Weierstrass theorem. Hence, it could be appropriately suitable for time-invariant, finite memory, continuous and non-linear networks. Subsequently, it could be employed as a filter bank. They also deliberated numerous applications based on nonlinear ANC.

When employed the conventional LMS algorithm in speech improvement entities, there was a crisis of the MSE expanding with the accessible signal power straightly, so as indicated by Caiyun (2012). The WsLMS methodology, which refreshed the step size of the adaptive filter weight vectors by the output, was exhibited at first. To enhance adaptive filter execution, at that point, the CC-WsLMS practice recommended by the application of the WsLMS algorithm as a component filter in the convex mix of two adaptive filters. The simulated results outlined an exceptional working.

Das ***et al.*** (2012) presented a virtual microphone by incorporating the remote microphone system with FsLMS. The suggested methodology was assessed tentatively in the abrogation of chaotic noise in a one-dimensional duct. Secondary path had been processed the same way and it showed non-minimum-phase response, and subsequently, poor execution had been resulted in the conventional FxLMS contrasted with the proposed FsLMS based design. Likewise, the proposed algorithm outflanked the FxLMS based remote microphone method under the causality limitation (when the propagation delay of the primary path was more prominent than the secondary). The various tests were exhibited to think about the execution of the FsLMS based virtual ANC.

George and Panda (2012) introduced an innovative algorithm called filtered-su LMS algorithm, which was based on an ANC system and the main aim of the algorithm was to enhance the convergence performance. The algorithm performed a combination between the IIR filter and a FLANN. The test showed that there was an enhancement in the operation.

George and Panda (2012a) defined a FLANN based multichannel nonlinear ANC network controlled by utilizing the PSO algorithm, which was appropriate for nonlinear acoustic practices. The utilization of the PSO algorithm decreased the dispute of local minima along with the elimination of costly designs for the transfer functions. The main disadvantage was that it was devoid of scalability.

Kadam and Fatima (2012) discussed the comparative analysis of the performance of two control algorithms for the termination of unwanted noise signals. The fundamental principle of that approach was inserting an anti-sound into the surrounding, and hence the undesirable noises were terminated. The outcomes symbolized that the anticipated algorithm could efficiently regulate the noise.

Kajikawa ***et al.*** (2012) discussed the basic ANC algorithms and their analysis. Hence the current advantages on the algorithms of signal processing, the methodologies for execution, the issues related to the implementation of novel applications as well as the shortcomings and the advancement of ANC networks were deliberated by them.

Sciuranza and Carini (2012) derived a bounded-input bounded-output (BIBO) stability criterion for FLANN filter based on the trigonometric functions. The basic principle behind that approach was that the FLANN filter was unaffected in case of any instability occurred on every occasion, and the recursive portion of the filter would be stable. The anticipated methodology was rapid in action compared to the other approaches.

Singhal ***et al.*** (2012) defined an ANC methodology utilizing higher order X-LMS filter, and that approach was based on traditional ANC strategy. Through that, the broadband noise was terminated from the degraded speech signal, and the impact of sinusoidal noise were also not measured. Sinusoidal noise could be inserted in the speech signal using diverse sources.

Chan ***et al.*** (2013) defined an innovative algorithm, namely, regularized transform domain normalized least mean square (R-TDNLMS) and its performance was examined. The anticipated algorithm diminished the discrepancy of estimators owed to the depletion of the excitation over a particular band of frequency. Otherwise, the occurrence of errors was due to designing, which in turn dropped the mean square error (MSE). In order to choose the regularization constraint, a novel input of white Gaussian was anticipated that led to the advancement of variable regularized Transform Domain Normalized Least Mean Square (*TDNLMS*).

Engelbrecht (2013) conducted an advanced empirical comparative study of lbest and gbest algorithms regarding PSO algorithm on numerous restrained minimization problems of distinctive intricacies. However, the outcomes of the investigation showed that not any of the two algorithms were appropriate for any problems and not even for any particular class of problems, which was the main disadvantage of the proposed approach.

Lin and Ho (2013) presented two methodologies in association with LMS and ANC algorithm entitled as normalized FxLMS algorithm to deal with the inconvenience of a reference signal. The proposed methodology decreased the disturbance of the signal and consequently improved the performance of the system.

Roy and Morshed (2013) explained the filtered-X least mean square (FxLMS) algorithm along with feedback in the ANC system. It offered innovative assembling as a means of improving noise reduction. The principle of the ANC was that a secondary noise was inserted so that it terminated the disparaging interference of the primary noise in the environment. The main drawback was that the steady-state termination response might be non-uniform for entire frequencies, especially during practical applications.

Zhao ***et al.*** (2013) described an adaptive convex association strategy based on FLANN filter in order to improve the tradeoff amongst the steady-state error and rate of convergence. The combining constraint regulated the association strategy in order to decrease the error of the entire filter by ascent methodology.

Chang and Chu (2014) examined an innovative ANC approach using an inconsistent tap-length along with an FxLMS step-size algorithm, which was based on the supposition of a two-sided and asymmetric exponential decay response design. The results confirmed that the planned methodology could provide significant progress in noise reduction ratios as well as in the rate of convergence. The main disadvantage of the planned approach was that there were certain differences about the applications, which were also discussed by them.

Hong (2014) had presented an ANC technology. S-LMS computation was proposed to explain the issue of the MSE with the assortment of the helpful power of the signal directly. The parameter changed the step size of the weight vectors for the adaptive filter as per the output of the given framework. At that time, the S-CLMS was considered to improve the adaptive filter by using switched adaptive filters. The simulation determined that superior performance and an improved result of signal action were achieved using S-LMS compared to LMS or the S-CLMS algorithm.

Kim ***et al.*** (2014) described a high-order lattice adaptive notch filter that could trail numerous sinusoids and was utilized to implement on a narrow band of ANC to terminate the impact of any inconvenience in the reference signal. The results validated the robustness of the anticipated methodology.

Xu ***et al.*** (2014) proposed an anti-audio interference ANC based on FxLMS variable microphone using anti-audio interference algorithm, which utilized an additional audio path to repay the impact of the interference of audio of the ANC filter. The anticipated algorithm reduced the intricacy in computation compared to the conventional algorithms.

Djigan ***et al.*** (2015) defined a system named hybrid ANC network, which was the association of feed backward (FB) and feedforward (FF) ANC networks. The algorithms utilized in their methodology were the RLS and LMS algorithm. The efficiency of the network was illustrated with the utilization of RLS as well as LMS algorithms.

Sun ***et al.*** (2015) defined the characteristics of employing the FxLMS algorithm employed mainly in the ANC to replace the monotonous effect of acoustic noise. In their approach, the path of the secondary was considered as a pure delay model for shortening the derivation. The examination validated the outcomes of executing ANC with the anticipated algorithm and could be utilized in industries. The main drawback was that the methodology was devoid of a normal path of secondary, impulse path divergence and modelling error of the secondary path were also not considered.

Biradar ***et al.*** (2016) used an effective optimization technique and a time matching method to reduce the order of the model.

Chang (2016) analyzed the disturbance impacts on narrowband ANC (NANC) and proposed altered forms to upgrade both the transient and steady-state execution. A delay less bandpass filter bank was intended to take out-of-band disorder in the created each error signal for refreshing the corresponding adaptive filters. Hypothetical examination and enhanced execution were checked by simulations utilizing estimated transfer functions from the trial setup.

Gomathi ***et al.*** (2016) suggested FxLMS algorithm for enhancing the rate of convergence of the ANC network by utilizing a variable step algorithm. The anticipated algorithm diminished the noise along with the enhancement in the convergence rate. A MATLAB simulation had been used to examine parameters.

Lam and Gan (2016) demonstrated practical mitigation for terminating the noise for safeguarding the health of the upsurging population. ANC methodologies could eliminate low-frequency noises without disturbing the ventilation. In addition, this methodology was more economical and more feasible because of the dominant efficient algorithms.

Liu ***et al.*** (2016) examined a WSN integrated ANC network, which decreased the noise level in the incubator of an infant at the ear of an infant as well as contributes WSN amongst the caregivers and the infant at both within and outside the neonatal ICU. The ANC approach was utilized to reduce noise.

Mirza ***et al.*** (2016) introduced Filtered x State Space RLS (FxSSRLS) methodology, which was an adaptive algorithm for ANC. Simulation outcomes validated the advanced performance of the anticipated algorithm, and it showed that it was better than other similar methodologies in terminating high-peaked impulses as well as in terms of stability and convergence rate.

Pan ***et al.*** (2016) presented a general process of learning the exact associations for random frameworks. The anticipated methodology chiefly focused on the propagation of error, and the main dispute of local minima was not a major concern of that application.

Rout et al. (2016) hosted a methodology to resolve the problem of non-linearity in saturation coupled to loudspeakers as well as microphones of ANC networks. To eliminate the nonlinearity due to saturation impact, a PSO algorithm could be utilized to tune the constraints of FLANN network entitled as PSO algorithm based nonlinear structure (PSO-NLS). A sensitivity analysis was also discussed to address the impact of various constraints.

Cheer and Daley (2017) proposed numerous applications regarding the ANC in which substantial control of noise utilizing conventional actions for controlling noise. Hence, they aimed at advancing the efficient characteristics of the substance while employing the ANC in a duct and established a connection amongst the acoustic substances and ANC networks.

Kean (2017) described a noise control approach for attenuating the duct and cabin noise as well as numerous advantages and disadvantages while employing the anticipated methodology. The main shortcomings of the approach involved the absorption of active noise, the structure of intelligent acoustics as well as the isolation of active noise.

Lam ***et al.*** (2017) examined an ANC network as a resolution of noise control in an open window. Hence the anticipated network was implemented at the entrance of a window, and the major objective was to attenuate the noise although sustaining the principles of ventilation in an open window. Since the approach was still on its initial phase of research, that was the limitation of that approach.

Lee ***et al.*** (2017) presented an ANC network encompassing a speaker and numerous processors programmed for executing a delay less sub-band FxLMS algorithm. The algorithm produced a spectrum of uniform gain and moderately attenuated the noise signal through the speaker output.

Murao ***et al.*** (2017) established a methodology known as multichannel ANC (MCANC) network for alleviating passing of noise via open windows. However, the principal principle in the research was the preprocessing. It was referred to as mixed error method, as a mixed error method could reduce noise entirely.

Sahib and Streif (2017) discussed the advancement of improved eco-friendly automobiles by the implementation of an efficient noise attenuation methodology based on ANC. The anticipated methodology eliminated the utilization of other passive techniques for reducing the noise, and hence there would be a considerable decline in the weight of the automobile.

Shi ***et al.*** (2017) hosted an active noise terminating window, which was an application of ANC network. The objective of the methodology was to maintain a pleasant and peaceful environment, although conserving the room ventilation. Here the algorithm used to be the minimax algorithm since LMS required more power for computation. The main advantage of the minimax algorithm was the decreased intricacy for computation, but the drawback was that it had a very slow speed of convergence.

Sun ***et al.*** (2017) defined an advanced variable step-size NLMS algorithm, which encompassed other conventional algorithms in terms of the rapid rate of convergence and reduced steady-state error. The anticipated algorithm varied the step size using time of iteration as well as a current error with very simple and efficient computation.

Tanaka ***et al.*** (2017) examined a binaural ANC network mainly implemented in industries to terminate the noise and the right and left ears of the worker occupying in the production line encompassed the control points. Hence, the ANC network employed the parametric array loudspeakers along with the FF array.

Xia ***et al.*** (2017) applied two commonly employed algorithms such as FF algorithm and PSO algorithm to various complex applications. In order to exploit the benefits of the anticipated algorithms, a hybrid optimizer based on these algorithms was proposed, which was named as PSOFF. It outpaced the two algorithms.

Zou ***et al.*** (2017) established the current and comprehensive analysis for ANC particularly focused on three distinctive ANC approaches based on diverse states of the application. The anticipated research was employed in order to control the noise of transformers and hence the design methodologies along with the discussion of the benefits and shortcomings.

Long-established ANC configuration intended to constrict the energy of residual noise, which was indiscriminate in the frequency domain. In any case, it was important to hold residual noise with a predetermined spectrum to fulfil the prerequisites of human discernment in a few applications. Jiang and Li (2018) presented the advancement of the ANC, and the sound quality was quickly examined. Their method underscored the headway of ANC strategy in the previous decades as far as improving the sound quality.

Zhao ***et al.*** (2018) proposed an ANC network to terminate the mid and low-frequency acoustics since most of the methodologies were focused on regulating the high-frequency noises. The algorithm used there was the FxLMS algorithm. The network performance of ANC could be checked under a train of high speed. The ANC could reduce the lower frequency signal within the vehicle.

Ho and Shyu (2018) defined advanced audio assimilated adaptive feedback ANC methodology. Conventionally, the ANC methodology eliminated the entire power of the undesirable noise around the whole spectrum, and the anticipated approach was utilized to provide the anti-noise in an audible range of frequency only to save the consumption of power and efficiency.

2.2 RESEARCH GAPS

Research gap 1:

- The MFsLMS algorithm can decrease the computational complexity of the FsLMS.
- The McLaurin series can relax the functional expansion of the MFsLMS algorithm.
- The stability of the ANC system can be evaluated via the hybrid algorithm.

Research gap 2:

- The hybrid filter can enhance the convergence and the effectiveness of the ANC system.
- FF algorithm can be used here for the identification of filter coefficients. The optimized value of filter coefficients can make the system into an efficient one.
- The use of optimized coefficients can obtain the faster convergence of the filter.

2.3 AIM OF RESEARCH

- To reduce the primary noise, the secondary noise is generated with the same magnitude and opposite phase.
- To reduce the nonlinear effects such as saturation and distortion presented in the signal and mainly suited in low frequencies.

- The computational complexity is the major issue in the existing one, and the computation is performed under three steps like generating the control signal, filtering the reference signal and up-gradation of controller weights as well as it can limit the low-frequency noise.

2.4 OBJECTIVES

- To propose a method for the design of ANC system using a suitable modified filtered algorithm for the reduction of noise.
- To analyse the stability of the ANC system.
- To verify the performance of the system.
- To introduce an approach for the effective diminution of noise.

2.5 ORGANIZATION OF RESEARCH

Chapter 1**:** In this chapter, the ANC has been introduced.

Chapter 2**:** This chapter presents the details of the literature review of ANC.

Chapter 3**:** This chapter presents existing optimization methods for active noise reduction.

Chapter 4**:** This chapter presents a method to the design of the ANC system using a modified filtered s least mean square algorithm for the reduction of noise. (Objective-1)

Chapter 5**:** This chapter presents the analysis and stability of the ANC system and also presents the performance of the system. (Objective-2 and Objective 3)

Chapter 6**:** This chapter presents the design of the ANC system with the effective diminution of noise using hybrid FLANN and FIR filters. (Objective-4)

Chapter 7: This chapter presents the overall conclusions and future scope of research in ANC.

References

2.6 SUMMARY

This chapter discussed the literature survey of the work done in the field of active noise control. This chapter also described the work done in the field of ANC using different algorithms. This chapter also discussed the research gaps, objectives and the organization of research.

CHAPTER 3

EXISTING OPTIMIZATION METHODS FOR ANC SYSTEM

3.1 ANC

The fundamental knowledge about the ANC has already been known for more than 70 years. The concept of ANC converted from an academic environment to productive scheme. It is one of the hopeful research areas in computer innovations and developing electronics in the late 20th century. In addition, ANC has useful in practical applications. Earlier attention of research in ANC had not been paid. The attention of research in ANC in starting in 2008, and an innovative area of application was created, and the systems used began to become more efficient. The approach can be classified in two stages. Initially, the scheme concentrating on the enhancement and growth of the filtering technology for the noise present in the source, electro-acoustic components and control process. To eliminate the undesired existing sound area, the ANC includes the electroacoustic generation of a sound field. The producing anti-noise signal with an equal amplitude can reduce the noise with the opposite phase, which provides a substantial reduction in the noise level (Zhao ***et al.***, 2018). The superposition of waves gives the concept that the two waves with matching phase and same amplitude have an additive effect, which delivers the doubling of the overall amplitude. At the same time, the two waves with similar amplitude but opposite phases have a subtractive effect, which yields a reduction of the overall amplitude. The phase denotes the corresponding location of the wave in its increasing and decreasing cycle. The waves fall and rise together if two waves are in phase. If two waves are out of phase, they cancel each other. By adding the accurate opposite sound, the ANC scheme goes to eradicate the sound components. For the amplitude and the phase of the anti-noise signal, the extent of the reduction is tremendously dependent on the accuracy of the system. The ANC system has a reduced installation volume and also acts at low frequencies with great efficiency. The approach can be used to integrate with a passive scheme, and it has several applications, which yields the hybrid control systems (Riyanto ***et al.***, 2007).

The effective electronic technique active noise control is used to decrease the effect of the noise. The creation of the anti-noise is typically similar in magnitude and opposite in the phase of the noise. Anti-noise and the noise are harmfully interfered to eliminate the effects of the noise. At the same time, active and passive noise cancellation may be applied individually.

Both cancellations are frequently combined to achieve maximum efficiency in the cancellation of noise.

The single-channel control system comprises a microphone sensor, control system, speaker and adaptive filter. The microphone sensor is used to sample the disruption. After giving the input signal, it can create the control signal. The control signal focused a loudspeaker on generating the anti-noise. The error microphone is to deliver the criticism to the controller, and it can alter itself to diminish the subsequent sound output.

An adaptive system can adjust itself depending on the reference signal modification, which provides the feedback via the error microphone to the controller.

The active noise controlling theory is described as below.

By using the electro-acoustic means, the active noise cancellation can be stated as noise reduction. By creating the anti-noise signal, the surplus noise is decreased and replicating the generated anti-noise signal. ANC is a critical intrusion of harmonic sound waves. Since the noise is harmonic, there are restrictions on the ANC applications in various domains.

The critical superposition of noise and the control signal is produced by the anti-noise signal. From this noise, it is critical to process noise and anti-noise in a harmonic signals collection. Consequently, it is important and needs high performance. Thus, the produced control signal should be acoustic waves. The performance of the ANC system is dependent upon the control system that provides the anti-noise signal. The electro-acoustic system requirement is suitable for the control system with noise source obtainable for hardware and software. The control system is mainly used to convert analog to digital and digital to analog signals. Acoustic, non-acoustic sensors, amplifiers, pre-amplifiers and loudspeaker are generally composed by an ANC. All these elements must be selected in a reasonable manner to suppress noise to confirm that the system is operating correctly at ambient settings.

The controller should change features of the noise depending upon the environmental situations at the same time. The systems can be separated into two groups named as feedforward and feedback. These two groups are estimated the control system with respect to traffic noise, computation power and hardware. The difference between the feedforward and feedback control process is essential in the concept of the ANC. These variations significantly affect the components, hardware cost and overall performance as well as capturing the genuine noise to measure the anti-noise. The reference signal is captured with feed-forward system to the controller. So, it is using an additional microphone. The active feedback systems provide the reference signal to the controller and this signal uses the secondary microphone to compute the original noise.

3.2 CLASSIFICATIONS

ANC contains two systems, such as feedforward and feedback systems. The feedforward system needs an extra position microphone to attain the early reflection of the noise wave. The feedback system estimates the noise wave internally. The system cannot work properly if the error microphone and secondary source are situated from the control point. The feedforward scheme can be trained to perform the immovable coefficient execution (Kajikawa ***et al.***, 2012). The error microphone was removed in the fixed coefficient process at that time, and the reference microphone remains in the way the noise wave. Typically, the single channel ANC system uses a low frequency source and a single control point. At the control point, the noise reduction is attained while the secondary source is unidirectional. Still, a spillover of the anti-noise wave pointers to increase the noise levels in other regions. The overall noise reduction is unbalanced when the single-channel system is applied to target more than one control point. Otherwise, the dual-channel system uses two secondary sources. Each source has one control point. In the execution, the crosstalk develops a mandatory issue and brings additional computational cost on top of the spillover problem when the secondary sources are unidirectional. Several benefits are obtained by using directional loudspeakers as the secondary sources in ANC schemes (Kuo and Morgan, 1999).

Traditionally, ANC is classified into two categories, such as local ANC and spatial ANC. In local ANC, the target area is defined locally as some specific points in space. While in spatial ANC the aim is to achieve the noise reduction spatially in the large space. Spatial ANC seems more beneficial as compared to local ANC, but physical and practical constraint makes it more complicated for implementation. Similar to the quiet zone, the noise source also has two categories point source and spatial source.

a) Point to point ANC

The point to point ANC is the most efficient and simple model of ANC systems, and the noise source is located in a small area, and the target region is local.

Feedforward ANC: These controllers are the major active noise controller, which cancels the broadband noise and narrowband noise (Olivares, 1998). Additionally, the feedforward control felt the reference noise before distributing through the speaker of cancellation (Widrow and Stearns, 1985).

The ventilation and exhaust systems produce an amount of broadband noise in ducts. The reference sensor captures the undesirable signal in this configuration at an earlier point source control, and it then feeds a controller to obtain the noise cancellation at a later point. In other words, a microphone measures a reference signal near the noise source before it moves over the loudspeaker. The reference signal used by the digital controller generates an equal amplitude signal and incident signal opposite phase. The important aim of the feed-forward controller is expecting the physical phenomenon in a predictive way through the data taken by the reference sensor. So, the noise is cancelled when going through an error sensor. The residue, i.e., the error signal measured by the error microphone is used as a performance index of the controller to adapt the filter coefficients.

An acoustic duct is the best example of point to point ANC, and this is the most cultivated areas of the ANC. The acoustic noise signal is picked by a reference microphone, which is processed by an electronic system (phase inverter and delay), to generate an anti-noise with the secondary loudspeaker that is same in amplitude but opposite in phase of the primary noise. At the position of error microphone, these two noises cancel each other to form a local quiet zone. This model is called feedforward ANC. The electronic system must be adaptive to rectify the non-uniform amplitude and phase response of the amplifier, filter, and transducers to achieve a satisfied noise reduction. The second-most important factor in satisfying the performance is the casualty conditions. After picking the reference signal, the controller takes some time to process and generate an anti-noise signal through the cancelling loudspeaker. If the electrical delay from the reference microphone to the loudspeaker is larger than the acoustic delay, it significantly degrades the performance of the ANC system. However, it performs well in case of periodic and narrowband noises. In the event of broadband noises, it is necessary to model the secondary path for compensating the electrical delay and meet the causality conditions. A large number of secondary path modelling techniques are available in the literature, FxLMS and variants are the most adopted.

Feedback ANC: FxLMS based feedforward ANC system uses two sensors, i.e., reference sensor and error sensor to attenuate the noise. The use of the reference sensor is not the perfect solution either from a microphone or any other type of non-acoustic sensors in many real-world applications. These limitations promote the feedback application ANC system, which only uses an error sensor. The principle of the feedback ANC system is using the measured error signal to synthesize the reference signal. The feedback ANC system has two loops, adaptive algorithm loop, and controller loop. The interface among these two loops obscures the analysis of the system. The steady-state weight update analysis of the adaptive filter for the feedback ANC system is useful (Sakai and Miyag, 2003).

Hybrid ANC: The third type of ANC system is the hybrid system. The feed-forward part of a hybrid system is used to evaluate and cancel the noises, associated with the reference signal. The feedback part of a hybrid ANC system only deals with the uncorrelated noises. The hybrid system with lower-order FIR or IIR filters has low computational complexity and achieves the same performance as feedforward and feedback ANC system alone. Therefore, hybrid ANC is more suitable for a large number of broadband and narrowband noise-cancelling applications. An adaptation process of the hybrid system has been increased by the modified hybrid model (Djigan ***et al.***, 2015).

b) Point to zone ANC

The noise source is localized in point to zone ANC, and the essential quiet zone is spatial. The best approach to mitigate the noise is to embed the ANC system in the noise source application (i.e., engines, turbines, fan, and vacuum pump) or at least placed it very closely. Narrowband ANC and 1x2x2 multi-channel ANC are the best suitable applications for this category.

Narrowband ANC: The system employed for cancelling the periodic noises is called the narrowband ANC system. In applying applications, this noise generated by rotating (or recurring) machines, for example motors, is mostly periodic. The single channel ANC system uses the non-acoustic sensors to cancel these narrowband components. These sensors like, accelerometer and tachometers synchronize internally generated sinusoidal reference signal. The frequency of internally generated primary noise is different from the actual primary noise because of the time-varying characteristics of the noise sources. This frequency distinction between essential noise and an inside produced reference signal is called frequency mismatch in narrowband ANC system. The only 1% of frequency mismatch can seriously debase the execution of the narrowband ANC system. The adaptive notch filter has the capability of tracking the time-varying frequency of the narrowband interferences by using an internally generated reference signal, and it offers easy control of the bandwidth. When sinusoid drifts slowly in frequency, an adaptive notch filter is beneficial. The steady-state performance is improved by using the bandpass filters to split the full-band error signal into multiple band limited sub-band error signals according to frequencies of reference signals. The convergence rate of the parallel narrowband ANC is enhanced by using the delay less filter-bank to segregate the full-band excitation and error signals.

Multichannel ANC: Sparsely distributed noise source components in a large dimension duct or an enclosure of an industrial noise field are more complicated than the single channel point to point ANC so that there is a need to use a multichannel active noise control (MCANC) system. Some of the best-known applications of a point for zone MCANC systems are impulsive and total noise in automobiles, propeller-induced noise in helicopter/plane cabins and heavy moving machinery at a construction site. More than one error sensor is needed to achieve a noise reduction in a big enclosure and automobile cabin. In MCANC, the location of each error sensor plays an important role in the proper estimation of total acoustic energy. A practical approach is to use the secondary source close to the primary noise source. In last one decade, many techniques and algorithms have suggested more efficient realization of MCANC system, of which Affine Projection Algorithm, MC-RLS, wave field synthesis, and higher-order ambisonics are famous for achieving spatial sound field control. The 2D higher-order ambisonics control, sparse FxLMS, and optimized time difference based reference microphone techniques are more advanced methods for the scattered sound field.

c) Zone to point ANC

Zone to point ANC is the case, when the noise source is distributed everywhere (i.e., offices, bedrooms, aeroplanes, marketplaces) and the targeted quiet zone is local. Active headphones, ANC headrest, ANC pillow, ANC helmet, and ANC infant incubator are the typical examples of a zone to point ANC.

ANC Headphones: Wearable listening devices, such as ANC headphones, are popular and commercially most successful audio integrated ANC product. The design of ANC headphone is straightforward, but it has some practical constraint. The reference microphone to pick the reference signal is placed on the outside of the ear cup of ANC headphones. At the same time, the secondary source is positioned inside to make a quiet zone around the eardrum, and the error microphone is used to pick the residual error. Conventional methods have some drawbacks. When the range of the controller coefficients is too large, it is difficult to obtain an optimal solution. Secondly, it is also important to determine the controller structure and the number of poles and zeros in advance so that both robustness and performance can be provided.

ANC Headrest: ANC headphones are used to avoid the exposure of unwanted noises but wearing this kind of devices for a long time has been still uncomfortable. The major motivation is to implement the ANC headrest to surpass this drawback. There are some difficulties in implementation since the noise source is unknown, and the location is an open environment.

ANC Infant incubator: According to the WHO report, more than 15 million babies have a premature birth in a year, and this number is increasing day by day. These premature infants or preemies are cared for and monitored in an infant incubator in the Neonatal Intensive Care Unit (NICU) till they are considered fully developed and healthy. Vital statistics of baby and other parameters, such as humidity, temperature, and oxygen supply, are monitored by sensors and devices inside the incubator. High level of noises from these devices and other equipment of NICU such as fans, I-V pumps and warning sounds. Passive noise control methods are ineffective to mitigate low-frequencies, and they also have some implementation constraints. This method heightens the need for the ANC for infant incubators. Recently, wireless communication integrated ANC is further improved by using hybrid ANC (Liu ***et al.,*** 2016).

d) Zone to zone ANC

Zone to zone is the most challenging area of ANC as the noise is spatially distributed over the region and goal for achieving reasonable noise reduction in a huge area. Environmental noise exposure, such as the noises of the industrial and transportation infrastructures (railway station, highways, and airport) noises, has been linked to myriad health risks. Passive noise control is not always a viable and economical solution to mitigate these multidimensional noises. In such conditions, the noise field is very complicated, and MCANC is expected to remove multi-dimensional noises. In recent years MCANC algorithms and techniques have been widely investigated and implemented to limit the noise pollution in our homes, offices, and working environments. Noise reduction performance and computational complexity of MCANC are always a major challenge for large-scale practice. Active Soft Edge (ASE) and Active Acoustic Shielding (AAS) are new promising techniques to mitigate the noises in the open window and large ventilations.

Active Acoustic Shielding: AAS is based on the principle of the ANC to attenuate the noises passing through an open window. The basic model of AAS is a set of ANC cells in an array, and each cell has approximately co-located secondary speaker and error microphone controlled by the feedforward FxLMS algorithm. Initially, AAS was implemented on a small open window with a few cells and the performance of AAS with moving sound sources, multiple sound sources, and reflected sounds are extensively studied.

3.3 APPLICATIONS

Acoustic noise issues are more complex with developing knowledge and engineering. For health concerns and upgrading of quality life, the noise stages have come under the human surroundings. WHO categorizes the noise as being the second-worst environmental pollution cause of bad health. The industrial products of engines, fans, transformers and blowers produce the general acoustic noise. Passive techniques of earmuffs are ineffective to be very luxurious or massive. One of the multi-channel ANC application is an active noise cancelling window (Shi ***et al.***, 2017). The scheme provides a soft living environment while preserving the ventilation of the room. The typical multiple-error LMS technology difficulties in handling the too much computational power through the digital signal processor in the application of active noise cancelling window is used. The results show that the minimax scheme has a separate benefit in computational complexity reduction yet. It has a corresponding low convergence speed.

Within one-tenth of the noise wavelength, few applications of ANC systems concentrate on the local cancellation of noise from the error microphone. When the control of areas is big, the multi-channel ANC process is automatically arranged. With the numbers of reference microphones, secondary loudspeakers and error microphones, the computational complexity of the multi-channel feedforward ANC scheme is increased (Murao ***et al.***, 2017). In the large 3D spaces, the active control of noise is costlier as well as more complicated. An effective execution of ANC scheme is based on the practicality and various methods have been developed to reduce the computational complexity. ANC process offers the living surrounding while conserving the room for ventilation (Bhan ***et al.***, 2016).

The binaural ANC method has been established to handle with factory noise (Tanka, 2017). When the workers are sitting along the construction line, the control points are positioned in the area of right and left ears of their labors. The error microphones and secondary sources are not permitted to be located close to the employer because of security necessities are difficult in the factory. This means that the proposed ANC system uses the feed-forward framework. It approves the parametric array loudspeakers (PALs) as the minor sources. PAL is one of the directional loudspeakers. It can be produced by the narrower sound field when compared to the conventional loudspeakers. The error microphone can be eradicated once, and the recommended ANC scheme has been trained offline. Depending on the DSP execution, the binaural ANC scheme performance is effectively established. Employers suffer from noise-induced hearing loss in factories. Defensive measures are immediately needed to solve the issue as mentioned above. By passive noise control, verbal communication may be delayed. ANC appears to be the possible solution (Pan ***et al.***, 2016). Another name of the primary source is the noise source in the ANC scheme. The secondary source is also known as the control source that transmits an anti-noise wave with the same amplitude and opposite phase of the noise wave. At the control point, the noise wave cancellation can be attained where the error microphone is set up to make the ANC scheme a closed-loop control based on the superposition theorem. The PAL makes use of the effect of nonlinear acoustic to create an audio beam from an ultrasonic beam.

The traditional method of controlling noise of high-speed train includes the passive noise reduction methods of vibration reduction, sound simulation etc. It involves lower frequency components at 300 km/h. In controlling high-frequency noise, all schemes are effective. A project based on an ANC system is used to remove the low and mid-frequency noise. By way of FxLMS technology, the running phase of the system was executed. Within a high-speed train, the performance of ANC scheme was tuned with the help of testing. The results show that the system reduces the low frequency noise inside the vehicle. Measures of noise reduction and vibration are the main requirement in the high-speed trains. The results show that the internal noise of the high-speed trains is focused on the low and mid-frequency range. It is called sound absorption. On the low and mid-frequency noise, the insulation measures have less effect. By terminating the anti-noise wave with the support of a suitable array of secondary sources, the ANC can be obtained (Elliott ***et al.***, 2000). The secondary sources are interrelated via an electronic system for the specific noise cancellation scheme using a particular signal processing technique. The benefit of the ANC is that the extra mass is small, and the performance of low-frequency noise cancellation is the best. So, the ANC process is used in many applications like manufacturing and automotive industries.

In dwellings, the noise mitigation process conserves natural ventilation. It is an open window scheme. The attenuation performance requires the information of the physical limits to design an open window ANC scheme. It is the control source formation of the several variables to be enhanced. By analytically inspecting the performance of various physical arrangements of control sources, the physical limits are categorized. The process involves the diffraction effects of the window, which depends on the finite-element technique using a two-dimensional model. By locating the control sources far from the edges of the window, the better attenuation is attained in the simulation time. Additionally, for real-world execution with minimal performance degradation, the plane of control sources could be situated centrally. The attenuation can be used to deliver the number of control sources depending on the preferred level of attenuation. For several angles of noise incidence, the simulated attenuation is a function of frequency and window width. This evaluation supports to estimate the configuration with fewer amounts of control sources needed for dissimilar situations. A double-glazed window is a general noise mitigation measure. The installation of noise barriers has been effective, and these methods do not interpret well for heavily populated high-rise urban regions. The upper floors of a high-rise structure are typically not protected from noise and barriers just mitigate noise are in the shadow zone. The integration of the ANC system on the top of the noise barriers can improve the effective height of the barriers (Chen ***et al.*** 2011). The cost, land scarcity and visual aesthetics are different factors that control the implementation of the noise barrier. Ventilation is important for regions with hot and humid weather, and this element is commonly authorized by local administrations. In high-rise development, the measures of noise mitigation must be active while also preserving the acceptable natural ventilation.

The ANC system includes a speaker and processors programmed to implement a delayless Subband FxLMS control procedure. It includes variable bandwidth Discrete Fourier Transform (DFT) filter bank having many subbands such that the system, in response to a broadband white noise reference signal indicative of road noise in the vehicle, exhibits a uniform gain spectrum across a frequency range defined by the subbands and partially cancels the road noise via the output of the speaker. In many ANC applications, computational burden and slow converging speed caused by large reference signal eigenvalue spread are a concern. A delayless subband algorithm, which decomposes the signals from the full band into a set of subbands, has previously been introduced to improve the convergence property of the control system and for minimizing the computational complexity. A detailed derivation of a uniform delayless subband algorithm is introduced. Furthermore, the inherent limitation of the uniform DFT filter bank is discussed. This inherent aliasing effect may degrade system performance. Hence, a variable bandwidth delayless subband algorithm is used as the basis of an ANC system for various types of road noises. This algorithm may be capable of overcoming the aliasing effect of the standard delayless subband algorithm. This algorithm, in certain implementations, is effective and has a low computational cost. Numerical simulations were conducted for controlling the measured road noises to validate the performance of the proposed algorithm. The simulation results indicate that the variable bandwidth delay less subband algorithm is an option for broadband ANC system implementation. In one example, a vehicle has an ANC system, including a processor. The processor implements a delay less subband FxLMS control algorithm including a variable bandwidth DFT filter bank having a number of subbands such that the system, in response to a broadband white noise reference signal indicative of road noise in the vehicle, exhibits a uniform gain spectrum across a frequency range defined by the subbands and partially cancels the road noise. The delay less subband FxLMS algorithm may further include a uniform filter bank. Center frequencies of the variable bandwidth DFT filter bank may be offset from centre frequencies of the uniform filter bank by one half bandwidth of the uniform filter bank. A bandwidth of the variable bandwidth DFT filter bank may be less than the bandwidth of the uniform filter bank. A bandwidth of the variable bandwidth DFT filter bank may be at least one half the bandwidth of the uniform filter bank. The ANC system may further include a speaker. The ANC system may partially cancel the road noise via the output of the speaker (Lee ***et al.***, 2017).

For controlling noise, ANC is now being discovered as a potential solution that broadcasts via an open window. The process aims to offer acoustic insulation through active means. At the same time, the natural ventilation properties of the open window are considered. The open window ANC scheme has been described by using numerical techniques. There is a well-known developing field in the ANC system for domestic windows. In heavily populated urban areas, the motivation behind such schemes stems from rising concerns for the reason of noise pollution. Also, movements toward urban sustainability pressure, the significance of natural ventilation through open windows. The traditional noise insulation technique does not deliver enough natural ventilation through multilayer glazing. They are also unreasonable for tropical environments. The ANC has been developed for different window types for the reason of graphical and cultural differences. It can be categorized as partially-opened windows, fully open windows and ventilation windows (Lam ***et al.***, 2017).

ANC contains various applications where it is unreasonable to attain essential noise control level using state-of-art passive noise control treatments such as low frequencies. The benefit of similar performance has been gained in recent years through the use of acoustic metamaterials, which attains levels of noise control performance that are not reachable with logically occurring materials. The high levels of noise control performance are usually attributable to the dispersive properties of these metamaterials. Their conduct has been assessed in terms of effective material properties such as the bulk modulus and effective density. The performance of ANC systems is also frequency-dependent. Nevertheless, the links amongst these two advanced noise control methods have not been thoroughly investigated (Cheer and Daley, 2017).

In road traffic noise, noise pollution is a well-known developing technology. At the source of noise emission, the noise reduction can be obtained by using insulation measurement or anti-propagation. Measurement is regularly the inexpensive technique at the source. The growth of improved environmentally-friendly vehicles depend on the ANC scheme by recommending the efficient road interaction noise mitigation technique. ANC methods can reduce the noise directly at the tires with road contact points by installing actuators (i.e., loudspeakers) inside the vehicle. It will also reduce the noise propagating inside the vehicle and will hence eliminate the needs for passive noise reduction measures. As a result, the weight of the vehicles can be reduced significantly, thus requiring fewer resources for production and leading to efficient fuel consumption during operation (Sahib and Streif, 2017).

Since the technique of ANC is very effective for controlling the low-frequency noise, its application to transformer noise control has been studied by many researchers (Zou ***et al.***, 2017). The history and the present status for the active control of the transformer noise, especially focuses on three typical ANC strategies according to different application scenarios, including global control strategy, virtual sound barrier and active noise barrier have already been reported. The theoretical principle, the design method and the application of these strategies have been summarized and compared. The advantages and limitations are analyzed. Finally, further research direction is discussed in the practical engineering application of ANC of the transformer noise.

The open-fit hearing aids that permit air and sound into the ear canal have turned out to be famous as of late. Unluckily, they result in the noise leakage issue that bypasses the hearing aids toward the eardrum and will corrupt the quality of the desired signal. An altered audio-integrated adaptive feedback ANC system is used for open-fit hearing aids (Ho ***et al.***, 2018). Generally, the ANC framework attenuates the aggregate power of the unwanted noise over the entire spectrum. To increase the efficiency and save power consumption of hearing aids, a customized filter based on the hearing threshold of the hearing-impaired patient to generate the anti-noise in the audible frequency range has been proposed.

Meanwhile, significant advancement has been accomplished in such fields as the realistic utility, industrialization development and commercial popularization of the ANC, and this developed method presents a realistic and viable preference for the active control of ship noise.

The sound field evaluation, system setup and key techniques are summarized, typical examples of ANC based engineering applications including control of cabin noise and duct noise are briefly described, and a variety of forefronts and problems associated with the applications of ANC in ship noise control, such as active sound absorption, active sound insulation and smart acoustic structure, are subsequently discussed (Kean, 2017).

The main applications are explained below.

Duct Noise: In the area of cancellation of active noise, the duct noise is very important. This is because, below the cutoff frequency, the plane wave mode is the only propagating mode. This system is easier than three to handle with one dimension. It is expected that success in one dimension will provide a fundamental for success in free space. The flow impedance features of the ANC can be examined in the significance of duct investigation. In ducts, the ANC has delivered a solid proof for this system (Eghtesadi et al., 1986).

Cylinders: ANC system is well investigated in cylinders. It is flexible, and it is fixed in motion by external forces. The cylinder structure is designed in such a way that the noise will be transmitted to simulate the propeller noise. For the active control of the noise, different structures have been used within the cylinder.

Fuselage: In a cylinder, an ANC investigation of the aircraft fuselage is a natural extension of ANC systems. It has been observed that there are significant reduction of noise in the aircraft.

Fans: It gives the natural application of ANC producing a low-frequency tone, which is at a blade passage frequency and also because of forced airflow it produces broadband noise. To reduce pseudo-periodic noise, the ANC has been used. Predicting the next period quite precisely is possible when synchronizing the noise-cancelling apparatus with blade passage frequency. To invert the signal and cancel its noise, it becomes the simplest thing when the next cycle is known. There are several commercial systems available that are designed to reduce fan noise, especially in heating and air conditioning systems.

Transformer Noise: Because of large transformers, the problem of reducing low-frequency hum and also reducing fan noise is said to be a similar problem. Based on the control of fan noise, the ANC may be applied to the periodic signal when the basic frequency is obtained. An added benefit of not producing important levels of broadband noise is placed in the transformers. The active control of low-frequency hum is also shown, which can be very effective in decreasing hum (Angevine ***et al.***, 1980).

3.4 NOISE REDUCTION APPROACHES

There are so many strategies that are used to reduce the noise. Theoretically, the noise can be reduced at any position in the transmission path.

Near Source: Normally, it is used to cancel the noise originated at the source. By cancelling the highest frequency, which is having more than half wavelength, is used to reduce the sound radiation effectively (Nelson ***et al.***, 1987). By using the extreme environmental conditions, for example, high-speed airflow or intense heat positioning is prevented. As in the radiation from a panel, the source of noise cannot be especially localized. Through the path of the sound transmission and placing one or more sources in the proximity to the noise source, the near-source cancellation is attained.

Enclosures: It gives additional effective application, demonstrates the principle of a natural application of Huygen's principle. Either the sound produced outside the enclosure is prohibited from entering or it is prohibited from radiating inside the enclosure. For an ANC, enclosures have several advantages as environments.

Single Point: Active noise minimization is done using cancellation of noise at a single point, which is one of the most effective strategies. Even though the applications in this idealized case are inadequate, practically perfect results are reachable. This method is used by placing the microphone in the respective position for the noise attenuation and minimizing the noise at a particular point.

Free Field: The active cancellation noise is more difficult in the free field environment, but the free field is used in more application. This technique is dependent on Huygen's principle. A noise source is surrounded by secondary sources to prohibit wide-area radiation.

3.5 IMPLEMENTATION STRATEGIES

The system of implementation for ANC must be considered when the configuration for microphone and speaker placement has been determined.

Geometric Phasing: The geometric phasing is the simplest scheme of the ANC. The speaker inverts the signal at the speaker location from the microphone. The signal from the microphone is delayed and inverted so that it reaches the speaker at the same time as the original sound. The signal is not alternate between microphone and speaker when compared with the acoustic path. The signal has an effective negative time version of the signal and has a signal shortcut.

Filtering: From a noise-corrupted version of the signal, it is utilized to extract the signal of interest. The signal of interest extracted in an ANC is used to cancel the noise actively, and also it can be inverted. Noise and signals are separated by using Wiener filtering, which is used to sample the combined noise and signal of interest. From the sampled noise, a model of the noise is formed synthetically by using a priori information about statistics or noise. Then the inverted model is added to the original noise corrupted signal. Finally, noise is removed from the desired signal.

Synchrophasing: It has been utilized efficiently in an active minimization of the periodic noise, which has given by transformers and engines. In this strategy, the ANC system is directed to the synchronizing signal. This allows getting an accurate prediction of the signal from a current period. This signal can be inserted into the signal path to reduce the noise (Elliott ***et al.***, 1988).

Adaptive Filtering: This filter is used to improve the track deviations in the system. This method is commonly used for the ANC. The advantage of this filtering is automatic adjustment and minimization. It consists of two microphones instead of one. The microphone is located upstream from loudspeaker to get the noise-corrupted signal. Another microphone is positioned at the downstream from the speaker to get the error signal. The observed, noise-cancelled signal is said to be an error signal. It must preferably be silence. A model of corrupting noise and outputs at the loudspeaker is created by this filter. Determination of the error and samples of the noise-reduced signal is done by using the error signal. The adaptive filter is obtained from this information, and the filter model is modified to reduce the new error.

Although most research in the area of adaptive ANC has been done using finite impulse response (FIR) filters, there has been some work done with other digital filter models. Infinite impulse response (IIR) filter has been used in this study (Eriksson ***et al.***, 1987).

Although the LMS algorithm is the simplest and most popular, several other algorithms have potentially better performance. Rather than the statistics based on signal values in its computation, Recursive Least Squares (RLS) algorithm uses the exact signal values. A much quicker convergence rate is the result. However, there are augmented computational necessities with RLS scheme. There are several methods used to reduce the computational complexity. The computational speed for an RLS adaptive filter is improved efficiently by using the Kalman approach. In an ANC application, infinite impulse response (IIR) adaptive filters, adaptive lattice filters, and fast transversal filter (FTF) algorithms are being mathematically and experimentally estimated. Resonance suppression in ducts and enclosures, transducer signal-to-noise ratio enhancement, echo cancellation in auditoria, engine test-cell resonance suppression, automobile exhaust noise suppression and impulsive noise source attenuation are some typical applications (Eghtesadi and Garden, 1989; Fuller ***et al.***, 1989).

Time Variance: For the reason for a change in environmental conditions, fatigue requirements and wear on an engine, the features of the noise will change over time and being attenuated in most of the applications. This scheme is an essential one when executing the ANC systems. It may be sensible to physically alter the structure occasionally if the changes over time will be minimal. If the noise features change meaningfully, the scheme may be better to use an adaptive ANC system as it will alter these changes spontaneously.

3.6 METHODS USED TO IMPROVE THE STABILITY OF ANC SYSTEMS

State-of-art methods of suppressing acoustic noise using passive sound absorbers generally do not work well at low frequencies. At a rapid rate, the investigation of the ANC is evolving technology. Enhanced systems and innovative applications are always being exposed. Some of the present research is mentioned below.

a) New Applications

For internal combustion engines, the active muffler is designed. This silencer can reduce car noise while preventing backpressure on the engine.

b) New Actuators

The use of piezoceramic actuators in the ANC has been analyzed by new actuators. The piezoceramic actuator is to reduce the cost of the ANC, and this actuator is a more efficient actuator when it is compared with other actuators.

c) New Configurations

In ANC there are alternate arrangements of sound sources. These source arrangements can make the effective Huygen’s surface possible.

d) New Algorithms

In the current research, one of the most active areas is an optimized algorithm or new algorithms. By the variety of adaptive filtering techniques, most of the algorithms are being developed. An adaptive algorithm of the least-mean-squares based algorithm is developed. For the multichannel ANC, there are also some algorithms. For the more effective realization of a Huygen’s surface, this is important in the quest. The schematic diagram of a typical ANC system in a duct is shown in Fig. 3.1.

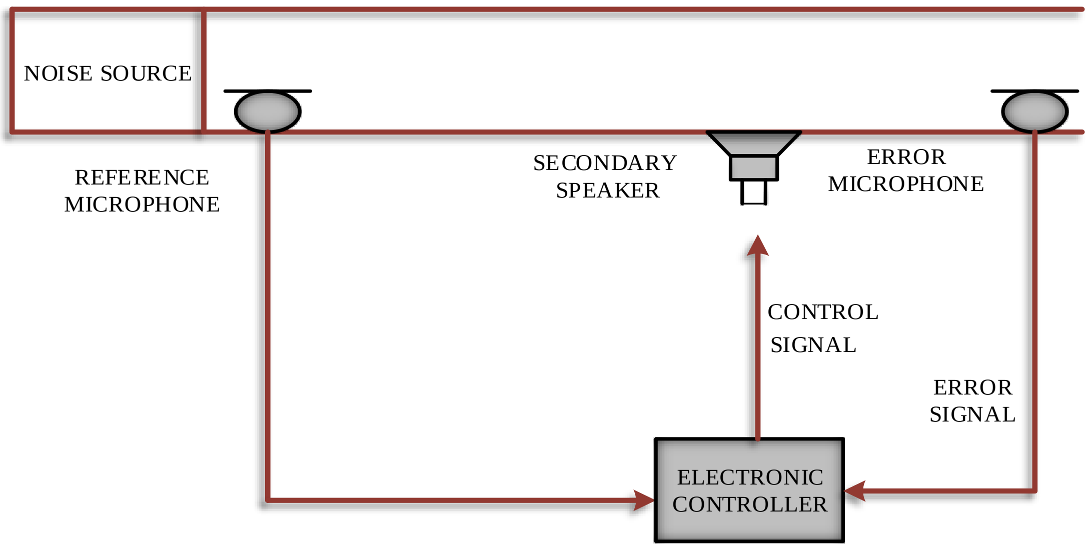


Figure 3.1: Schematic diagram of a single channel ANC

Before it falls out by cancelling the loudspeaker, by a reference microphone close to the noise source a reference signal is felt. For generating a signal of the same amplitude but 180^0 out of phase, the reference signal is used by the noise canceller. This anti-noise signal is used to ignite the speaker to nullify a sound, which attenuates the primary acoustic noise in the duct. The broadband feedforward method's fundamental principle is that the propagation time delay between the active control source (speaker) and the upstream noise sensor (reference microphone) offers the chance to acoustically reintroduce the noise at a position in the field where it causes cancellation. Between the loudspeaker and the microphone, the spacing must satisfy the principles of high coherence and causality, that is, the reference signal must be measured early enough so that at the time when the noise signal reaches the speaker, the anti-noise signal can be produced. To reduce the error, the residual error signal, which is utilized to adjust the filter coefficients, is measured by the error microphone. To manage the acoustic effects in the duct, real implementations need more attention.

For ANC applications, the FxLMS method is the most commonly used adaptive signal processing method, which is the modified version of the LMS algorithm. While many algorithms and control schemes that improve on certain drawbacks of the FxLMS algorithm have been presented, there is still room for improvement.

Due to the alteration of the noise source, degradation of noise components and changes in the environment, the controller has to be adaptive (Strauch and Mulgrew, 1998). The standard FxLMS algorithm has been applied to most conventional ANC systems, which is linear. For active control of narrowband and broadband noise, although less computational complexity is involved. Below the following situations, a linear ANC demonstrates performance degradation. The components of the ANC system may themselves have non-linearities, e.g. the loudspeaker can stimulate both the harmonics and frequency of interest. From a dynamic system, the noise may be deterministic and a “nonlinear noise” process. For example, fan noise often shows chaotic behaviour.

- ❖ Due to the nonlinear transfer function of the primary path, at the cancellation point, the primary noise may exhibit nonlinear distortion, e.g., with very high sound pressure, the primary noise propagates in a duct.
- ❖ Between the error microphone and the speaker, the secondary path transfer function may exhibit a non-minimum phase response.

Various methods have been suggested for the active control of non-linear sound processes. Since the FxLMS algorithm use the linearity feather of the controller, it is not possible to train a non-linear controller, different algorithms have been developed to polish the working of the ANC system. To control the non-linear noise process and to compensate the non-minimum-phase secondary path transfer function, a non-linear controller based on normalized Gaussian radial based neural network is developed. In the secondary path transfer function, to control the nonlinear effects, recurrent neural networks have also been utilized. For feedforward ANC very recent Adaptive Volterra filters have been introduced based on multi-channel structure, and it attains better cancellation performance for the following two conditions.

- ❖ The primary path exhibits non-linearity.
- ❖ While the secondary path transfer function has non-minimum-phase, using a reference microphone, the noise signal received is predictable and nonlinear.

Particle swarm optimization algorithm (PSO): It is a search algorithm, which is inspired using the social behaviour of the bird flocks. To solve the complex global optimization problems, the primary goal of this is the meta-heuristic algorithm depending on the inspiration from various sources to ameliorate fitness. According to the best solutions achieved by the entire swarm, each particle adjusts its position and to the best solution that it has found separately. Dealing with particular types of noises to acquire a set of constants that speed up the filter response is the main aim of PSO. The algorithm topology is the way that particles communicate with each other, which has a significant influence on the enactment. Star and the Ring are the two well-known examples of global and local topologies. All particles are fascinated by the best position found by the whole swarm in the former. Particles are subjective by best positions found by their neighbour particles in the second configuration. Often making the swarm vulnerable to be locked in local minima, convergence in the Global topology occurs prematurely. Instead, the ring setup shows good investigative properties, essential for better solutions. However, it tends to give a slower convergence (Engelbrecht ***et al.***, 2013).

Firefly algorithm: Based on the flashing behaviour of fireflies, it is a multimodal (Yang, 2009) nature-inspired metaheuristic algorithm. The main thing in this algorithm is the flashing light. Nearly every species of fireflies forms unique small rhythmic flashes, and by the process of bioluminescence, the flashes are being created. The brightness and the attractiveness decrease efficiently if the distance between the fireflies increases. Furthermore, the firefly will move in a random direction when it has not been able to find any more fireflies in its surroundings. A mutual coupling happens between the fireflies, while a firefly moves across another firefly.

FLANN: In nonlinear ANC systems, an efficient way of compensating non-linear distortions, the adaptive functional link artificial neural network (FLANN) based on FsLMS algorithm filter has received more interest recently. By utilizing the benefits of linear outputs-coefficients relationship and low computational complexity, the FLANN filters-based polynomial expansions, trigonometric functional expansions and piecewise linear expansions have been established in nonlinear ANC systems as adaptive controllers. In recent years, various types of FLANN filters have been proposed for enhancing the performance of non-linear ANC systems such as recursive FLANN, reduced feedback FLANN, nonlinear neuro-controller based FLANN, generalized FLANN and hybrid ANC system-based FLANN. It is important to note that the FLANN filters are the members of the class of causal, finite memory, shift-invariant, nonlinear filters whose output linearly relies on the filter coefficients.

New filters

As the performance is satisfactory, non-linear responsive filters should be used in the design of ANC systems.

An FIR filter has several properties that make it better to an infinite impulse response (IIR) filter.

3.7 Conventional FsLMS algorithm and its performance

In the ANC system, the essential way is an anti-noise, which can be extended utilizing Taylor series expressed by Eq. (3.1). The Taylor series expresses a function in the form of the sum of infinite terms.

$$P(n)=\sum_{t=1}^{T}\left(c_{t,0}x(n)+c_{t,1}x(n-1)+....+c_{t,m}x(n-m)\right)^{t} \quad (T\geq 1) \tag{3.1}$$

Where T is a form of approximate method, when T =1, the approximate method is linear, when T>1, the approximate method is nonlinear. In Eq. (3.1) input signal is $x(n)$, primary noise is, and functionally expanded vector is $c_{t,0}$. As a result of less computational complexity and simpler to design, it is generally utilized in ANC.

In ordinary FsLMS algorithm, reference signal *e(n)* is extended by trigonometric capacity initially, which can be given by Eq. (3.2).

$$\begin{aligned} &T_1(n)=[a(n),a(n-1),...a(n-N)] \\ &\vdots \\ &T_{2r}(n)=[\sin(r\pi a(n)),\sin(r\pi a(n-1)),...,\sin(r\pi a(n-N))] \\ &T_{2r+1}(n)=[\cos(r\pi a(n)),\cos r\pi a(n-1),...,\cos(r\pi a(n-N))] \end{aligned} \tag{3.2}$$

In Eq. (3.2), r is the order of primary path, $T_1(n)$ says the trigonometric function, and N+1 is the quantity of the input neuron. Every neuron set is handled autonomously utilizing the linear controller. For example, the FIR filter, the output of each filter is $y_i(n) \quad (1\leq i\leq 2P+1)$. In this manner, the overall output signal of FsLMS algorithm can be declared by Eq. (3.3).

$$\begin{aligned} y(n)&=\sum_{r=1}^{2r+1}y_p(n) \\ &=\sum_{\boldsymbol{r}=1}^{2\boldsymbol{r}+1}\boldsymbol{H_r}(\boldsymbol{n})\boldsymbol{V_r}(\boldsymbol{n})^{\boldsymbol{T}} \\ &=\sum_{j=0}^{N}h_{1,j}a(n-j)+\sum_{r=1}^{r}\sum_{j=0}^{N}\left[h_{2p,j}\sin(r\pi a(n-j))+h_{2p+1,j}\cos(r\pi a(n-j))\right] \end{aligned} \tag{3.3}$$

Evaluating Eq. (3.3), it can be realized that the initial segment of right is straight control term and the second piece of right is nonlinear control term. The Vector representation is $\boldsymbol{H_r}(\boldsymbol{n})$, expansion vector of a trigonometric function is said to be $\boldsymbol{V_r}(\boldsymbol{n})$, the output of primary noise

$y_p(n)$. By the Maclaurin extension of trigonometric capacity, the nonlinear piece of Eq. (3.3) can be extended as given by Eq. (3.4).

$$y(n) = \sum_{r=1}^{\Pr}\sum_{j=0}^{N}\left[h_{2P,j}\sin(r\pi a(n-j)) + h_{2r+1,j}\cos(r\pi a(n-j))\right]$$

$$= \sum_{r=1}^{r}\sum_{j=0}^{N}\left\{\begin{matrix} h_{2r+1,j} + h_{2r,j}\,p\pi a(n-j) - \dfrac{h_{2r+1}(r\pi)^2}{2!}(a(n-j))^2 - \\ \dfrac{h_{2r,j}(r\pi)^3}{3!}(a(n-j))^3 + \ldots \end{matrix}\right\} \tag{3.4}$$

Using Eq. (3.4) into Eq. (3.3), output signal y(n) is determined by a polynomial. Here, the auxiliary method is viewed as the non-least stage, and the optional noise is given by Eq. (3.5).

$$\sum_{m=0}^{M} s_m y(n-m)$$

$$= \sum_{m=0}^{M} S_m\left\{\sum_{j=0}^{N} h_{1,j}a(n-j-m) + \sum_{r=1}^{r}\sum_{j=0}^{N}\begin{pmatrix} h_{2r+1,j} + h_{2r,j}r\pi a(n-j-m) - \\ \dfrac{h_{2r+1,j}(r\pi)^2}{2!}(a(n-j-m))^2 \\ - \\ \dfrac{h_{2r,j}(r\pi)^3}{3!}(a(n-j-m))^3 + .. \end{pmatrix}\right\} \tag{3.5}$$

Where M and $\{S_m\}_{m=0}^{M}$ are the order and coefficients of the secondary path, and the secondary noise is stated by s_m.

By comparing Eq. (3.5) with Eq. (3.1), it is clarifying why the FsLMS algorithm can be utilized to mitigate nonlinear noise. Knowing from the Eq. (3.5) that the controller coefficients of the direct part are free, so the linear part of essential noise can be diminished well. Anyway, the controller coefficients of the nonlinear part are not free, the coefficients among even things and coefficients among odd things are variously related. In genuine essential noise, these various connections are not generally existing, so it is hard to adjust the controller coefficients of the nonlinear part and influence them to be figured precisely. Subsequently, in term of ordinary FsLMS algorithm, the execution of linear control part is superior to that of the nonlinear control part.

There are many enhanced variants of FsLMS algorithm; the most prevalent of them are generalized FLANN (GFLANN) algorithm. GFLANN algorithm has been proposed to take care of cross-terms issue occurred in FsLMS algorithm, yet for the coefficients issue of nonlinear parts isn't included. Subsequently, as FsLMS algorithm, GFLANN algorithm will not care about the coefficients issue of nonlinear parts.

3.8 CONVERGENCE OF ANC SYSTEM

A number of techniques have been developed for ANC systems. Among these, FxLMS algorithm is the most familiar adaptation algorithm used in ANC applications. A FxLMS algorithm with variable step size to develop the concurrence of the ANC, and this algorithm is mostly preferred due to its use as a controller in an adaptive filter to update the filter coefficients. This algorithm will improve the convergence as well as a reduction in noise compared with a conventional FxLMS algorithm, and this new technique is based on arctangent function. FxLMS algorithm can be favourable in interpretations of quick convergence mechanisms in specific ANC due to pre-filter gained signal, and a secondary path is used. The conflict among the convergence exactness fixed-step LMS algorithm and convergence speed can clear up by the variable step LMS algorithm. At the first stage of tracing and adaptive phase, the bulk step size has quick convergence speed, and little step for small, steady-state error when the algorithm is in steady-state. Some of the approximations are used, to control the step size in the adaptive mechanism. A simple and efficient technique is worn to adaptive error signal in the process, to provide some types of functions among the error signal and step size. Recently, the main variable step size algorithm is to develop the non-linear case among step size and error signal to alter the step.

An enhanced variable step-size NLMS algorithm has been proposed. The NLMS algorithm has quick assembly rate and low, steady state error contrasted with another conventional versatile filtering algorithm. Yet, there is an inconsistency between convergence speed and steady-state error that influences the execution of the NLMS algorithm. Another variable step-size NLMS algorithm can powerfully change the progression estimate as indicated by current fault and emphasis times. The proposed algorithm has a basic plan and effortlessly setting parameters, and viably solves the inconsistency in NLMS.

Since the recurrence and breeding characteristics of motor fumes blast are subject to the motor rotational speed, a flexible noise control algorithm ought to have a quick combination appearance. A viable ANC framework dependent on cross-section structure versatile channel is created for the control of car disable noise. The developed ANC framework is executed utilizing a DSP and connected to the active control of motor fumes commotion to demonstrate its wealthy control.

A structure for the execution of the ANC system with online optional way designing is created. This plan involves four comparative modules to diminish the undesirable essential noise. One of these module executes the primary adaptive control filter that uses FxLMS algorithms to link up the tap-weights. Two different modules function such as adaptive designing filters that utilize an LMS algorithm to show the auxiliary way filter. The last module fills in as a digital filter to deliver the weak noise gained signal. This fast execution of the ANC system results in a quick structure and quick convergence with the capacity to grow the four versatile filters and bus data when better noise decrease for ANC framework is wanted.

In the territories of acoustic research or applications that behave with not-correctly known or variable conditions, a strategy for adjustment to the uncertainness or changes is typically fundamental. While seeking a variation algorithm, it is difficult to neglect the least mean squares (LMS) algorithm. Its straightforwardness, speed of computation, and heartiness have won it a wide region of utilizations: from media transmission, through acoustics and vibration, to seismology. The algorithm, be that as it may, in any case, does not have a full hypothetical investigation. The most likely the reason for its primary disadvantage: the need for a cautious decision of the progression measure or, in other words, why such a large number of variable step size kinds of the LMS algorithm have been created. Novel computation adds to both the previously mentioned attributes of the LMS computation. In the first place, it demonstrates an inference of another fundamental condition for the LMS algorithm (Gholami-Boroujeny and Eshghi, 2008).

At the point when reference signals are defiled by broadband aggravations, the execution of the customary FxLMS algorithm is truly corrupted. Another narrowband ANC algorithm that can relieve the impact of the broadband aggravation is prsented (Bismor, 2012). The adaptive line enhancer (ALE) in light of an IIR step channel is used to enhance the SNR of the reference flag. A high-arrange IIR grid step channel has been proposed that can bolster effective following of numerous sinusoids, and it is joined with the filtered x gradient adaptive lattice (FxGAL) algorithm to acquire a computationally productive narrowband ANC computation with a quick intermingling rate.

The ANC system adaptive filters experience the ill effects of dependability issues within sight of hasty noise, and new techniques must be researched to conquer this restriction. Filtered-x state-space recursive least square (FxSSRLS) is SSRLS based viable and versatile algorithm for ANC. PC reproductions are executed to confirm the improved execution of FxSSRLS algorithm. Symmetric α-stable (SαS) dispersions are utilized to demonstrate imprudent noise. The recommended arrangement shows better strength and quicker assembly, without endangering the execution of the proposed arrangement as far as remaining noise concealment within sight of driving forces.

FMB-ANC is a technique insusceptible to crosstalk, enabling higher strength to precariousness and quicker combination than the Crosstalk Resistant ANC approach (CTRANC). This technique is productive for speech upgrade since it expels sensibly the relationship between the essential and references evaluated speech segments. In the FMB-ANC the subband noise estimation encourages the combination and expands the level of sinusoid retraction.

Two sorts of anti-audio ANC algorithms are dependent on an ordinary FxLMS-VM algorithm. FxLMS-VM-AI algorithm utilizes an additional sound way to make up for the impact of the sound impedance marvel on the ANC adaptive filter. The time-frequency mixed TFM-FxLMS-VM-AI algorithm can conquer this sound obstruction impact by computing the coefficients of the ANC adaptive filter in the recurrence area. The time-space acoustic wavefield recreation strategy is embraced to testing the execution of the proposed ANC algorithm in a sound obstruction condition. Both proposed computations demonstrate better assembly exactness as far as the adaptive filter coefficients and preferred sound signal execution over the ordinary algorithm.

Griffith's Variable step size algorithm has been utilized for ANC on ADSP-TS201 EZ-Kit Lite. The double computational units and execution of up to four guidelines for every cycle, which are uncommon highlights over different processors and are best used to produce an advanced code. The VGLMS gives enhanced auxiliary way estimation and computations included are negligible as a similar inclination is utilized for step-measure computation and coefficient adjustment. The enhanced optional way gauge enhances the ANC execution. Further, a versatile step-estimate algorithm is utilized for the fundamental way to accomplish quicker combination.

A unique parallel narrowband ANC framework with the neighborhood auxiliary way estimation is a propelled approach (Martins, 2000) to reduce the computational complexity of the parallel-shape narrowband ANC system and to offer a similar execution regarding noise abrogation and speed of concurrence. Rather than utilizing a solitary worldwide high-order FIR design, here it has been examined that how various neighbourhood low order FIR models might be utilized to get the sifted reference signals.

Another strategy for the optional online way presenting in the criticism ANC system is produced (Xu ***et al.***, 2014). In functional cases, the auxiliary way is normally a time-fluctuating. For these cases, web-based presentation of optional way is required to guarantee to intermingle of the framework. The suggested strategy comprises of two stages, a commotion controller that depends on an FxLMS computation, and a variable step-size (VSS) LMS computation has been utilized to adjust the used channel with the auxiliary way. With the end goal to expand the execution of the computation in a quicker intermingling and precise execution, the VSS-LMS computation has been stopped at the ideal point.

The algorithm depends on adaptive filtering with averaging (AFA) and utilizes a comparable structure as that of the FxLMS ANC system (Davari and Hassanpur, 2009). The algorithm, called FxAFA computation utilizes midpoints of two information and amendment terms to discover the refreshed estimations of the tap weights of the ANC controller. The proposed algorithm gives quick intermingling as contrasted and the FxLMS computation, for both broadband and narrowband noise signals. FxAFA computation is a superior decision for low computational intricacy and stable execution.

Two strategies proposed in blend with an LMS based ANC algorithm, named standardized filtered-x LMS/commutation error (NFxLMS/CE) algorithm, to manage the aggravation that is free of a reference flag. Another stochastic strategy to examine intermingling properties of the NFxLMS/CE algorithm under the impact of the aggravation is first settled (Tahir ***et al.***, 2003). It is given that the reference flag is steadily energizing of adequate request, exponential assembly of the algorithm is determined by a step-size condition. An exponential-decay step size (EDSS) is then proposed to acquire another ANC algorithm alluded to as an EDSS-NFxLMS / CE algorithm. Also, a disturbance-compensation (DC) system is created for the EDSS-NFxLMS/CE algorithm to get an EDSS-NFxLMS/CE_DC algorithm to such an extent that the impact of the aggravation can be lessened. It is demonstrated that the EDSS-NFxLMS/CE_DC algorithm is exponentially united.

3.9 BASIC STRUCTURE OF ANC SYSTEMS

Current dynamic sound control frameworks comprise of a control source used to bring a controlling sign into the acoustic system. This unsettling influence lessens the undesirable noise starting from the essential sources by adding to it a flag of some extent. The control flags that drive the control actuators are created by an electronic controller, which utilizes as sources of info, the critical mistake from the fault microphone. Dynamic noise control frameworks are generally utilized in the low recurrence go, for the most part beneath 500-600 Hz. At higher frequencies, passive control estimates, for the most part, turn out to be more financially savvy (Lin and Ho, 2013).

The major two kinds of ANC control system will be considered here:

- ❖ Adaptive filtering – the coefficients are modified adaptively to mitigate output error.
- ❖ Waveform synthesis- the type of feedforward control fitted with routine noise.

3.10 ADAPTIVE CONTROL

The standard strategy for assessing a signal debased by the added noise is to go it through a filter that tends to cancel the noise while leaving the signal unaltered, i.e., direct filtering. The structure of such filters is the space of ideal filtering, which started with the spearheading work of Wiener and was broadened and improved by others. Figure 3.2 shows the direct separating procedure.

Figure 3.2: Direct filtering

Filters used for direct filtering can be either Fixed or Adaptive.

Fixed filters – The plan of settled filters requires from the early learning of both signal and noise, i.e., If the signal and noise are known as in advance, the structure of a filter can be finalized that passes frequencies contained in the signal and rejects the recurrence band possessed by the noise.

Adaptive filters – Adaptive filters can alter their drive reaction to shift through the related signal information. They require next to zero from the earlier information of signal and noise attributes. Moreover, adaptive filters have the capacity of adaptively following the signals under non-stationary conditions.

Noise elimination is a variety of ideal filtering that includes delivering a gauge of the clamour by sifting the reference information. Afterwards, this noise gauge is being subtracted from the essential information containing both noise and signal.

It makes utilization of a helper or reference input, which contains a corresponded gauge of the noise to be dropped. The reference can be obtained by setting at least one sensor in the noise field where the signal is missing, or its quality is sufficiently powerless.

Subtracting noise from earned signal includes the danger of misshaping signal, and whenever done inappropriately, it might prompt an expansion in noise level. This necessitates the commotion gauge n' ought to be a correct copy of n. If it was conceivable to know the connection between n and n', or the attributes of the channels transmitting noise from the source of the noise to the essential and reference inputs are known, it is conceivable to make n' a nearby gauge of n by planning settled filter. Anyway, the attributes of the transmission ways are not known and are capricious; a versatile procedure controls filtering and subtraction. The henceforth adaptive filter is utilized that is equipped for altering its motivation reaction to limit a mistake flag, or, in other words, the channel yield. The change of filter weights, and subsequently, the motivation reaction, are administered by the adaptive algorithm. With versatile control, a decrease of noise can be attained with the risk of changing the signal. Adaptive noise control makes the conceivable fulfilment of clamor dismissal levels that are troublesome or difficult to accomplish by direct filtering. Figure 3.3 illustrates the noise cancelation block diagram.

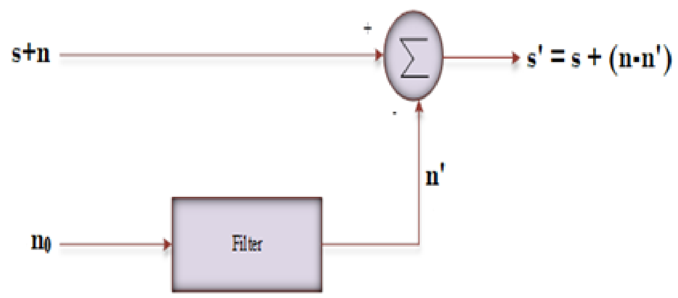


Figure 3.3: Noise cancellation

The fault signal to be utilized relies upon the application. The criteria to be utilized might be the minimization of the mean square error, the transient normal of least square error and so forth. Distinctive algorithms are utilized for every minimization criteria, e.g., LMS computation, the Recursive Least Squares (RLS) computation and so forth. The base mean-square error model can be utilized to comprehend the idea of adaptive noise elimination.

The adaptive controller is a controller that can change its tendency in light of changes in, all the while, and the unsettling influences happening progressively. An adaptive controller is a controller with movable parameter and a component for altering the parameters.

The adaptive control system incorporates a computerized filter with powerfully changing coefficients according to the prerequisite and with the adjustments in nature. Figure 3.4 is an ANC framework with an adaptive filter.

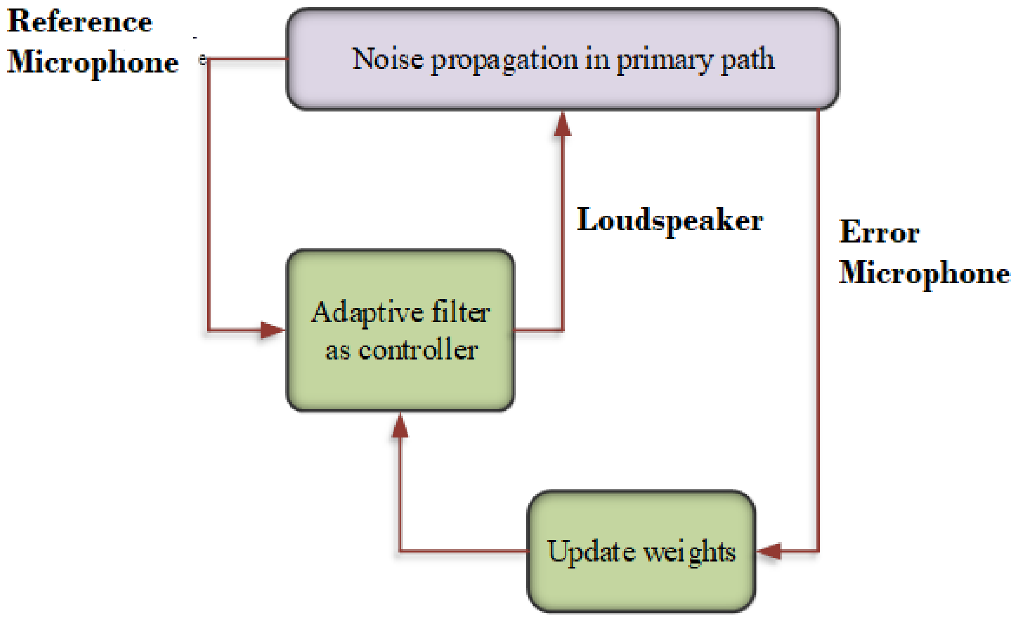


Figure 3.4: Active Noise Control System with Adaptive Filter

3.11 ADAPTIVE NOISE CANCELLATION

As shown in Fig. 3.5, an ANC has two inputs – primary and reference. The primary input receives a signal (s) from the signal source that is corrupted by the presence of noise (n) uncorrelated with the signal. The reference input receives a noise n_0 uncorrelated with the signal, but correlated in some way with the noise (n). The noise n_0 passes through a filter to produce an output n′ that is a close estimate of primary input noise. This noise estimate is subtracted from the corrupted signal to produce an estimate of the signal at s′, the ANC system output.

In noise-cancelling systems, a practical objective is to produce a system output s′= s + n- n′ that is the best fit to the signal s in the least-squares sense. This objective is accomplished by feeding the system output back to the adaptive filter and adjusting the filter through an LMS adaptive algorithm to minimize total system output power. In other words, the system output serves as the error signal for the adaptation process.

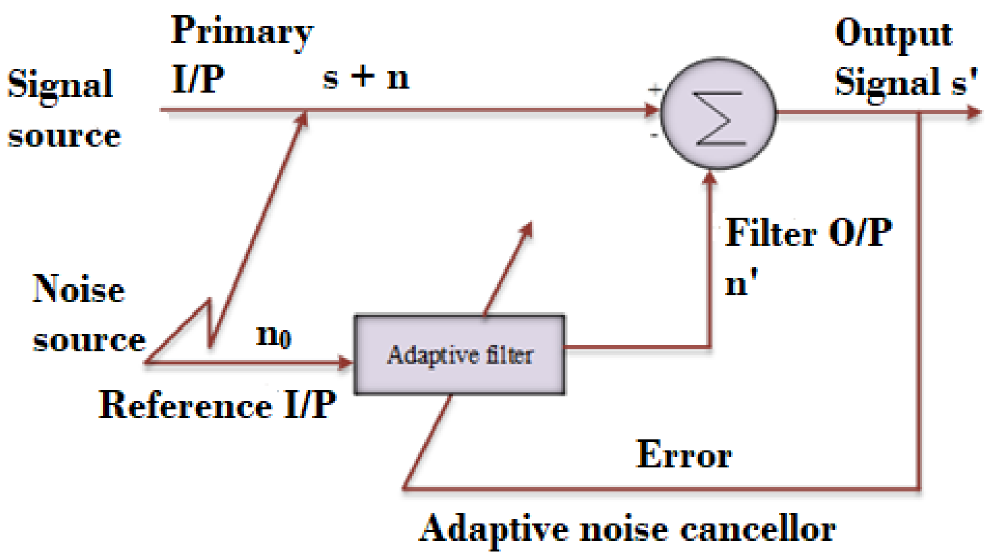


Figure 3.5: Adaptive noise canceller

Assume that s, n_0, n and n' are statistically stationary and have zero means. The signal s is uncorrelated with n_0 and n', and n_1 is correlated with n_0. Therefore, the following can be expressed.

$$s' = s + n - n'$$

$$\text{i.e., } s'^2 = s^2 + (n - n')^2 + 2s(n - n') \tag{3.6}$$

Taking expectation of both sides and realizing that s is uncorrelated with n_0 and n', Eq. (3.7) is obtained.

$$E[s'^2] = E[s^2] + E[(n - n')^2] + 2E[s(n - n')]$$

$$= E\left[s^2\right] + E\left[(n - n')^2\right] \tag{3.7}$$

The signal power $E\left[s^2\right]$ will be unaffected as the filter is adjusted to minimize $E\left[s'^2\right]$ and hence Eq. (3.8) is obtained.

$$\Rightarrow \qquad \min E\left[s'^2\right] = E\left[s^2\right] + \min E\left[(n-n')^2\right] \tag{3.8}$$

Thus, when the filter is adjusted to minimize the output noise power $E\left[s'^2\right]$, the output noise power $E\left[\left(n-n'^2\right)\right]$ is also minimized. Since the signal in the output remains constant, therefore minimizing the total output power maximizes the output signal-to-noise ratio.

Since $\qquad (s'-s) = (n-n')$

This is equivalent to causing the output s′ to be the best least-squares estimate of the signals.

3.12 ADAPTIVE FILTER

The term adaptive signifies that the filter weights are not fixed, rather these are adjustable according to the variation in the external environment. The weights are randomly initialized, and according to an adaptive algorithm, the controller updates its weights to minimize the residual noise at the listening side. An adaptive filter can be summarized as Filter parameters such as bandwidth and resonant frequency change with time. The coefficients vary with time and are adjusted automatically by an adaptive algorithm.

Coefficient Adaptation

- The purpose of determining the coefficients of the filter model is to maximize the statistical correlation between the reference signal and the coefficients.
- This, in turn, is done by minimizing the correlation between the error signal and the filter state as is relevant to the coefficients.
- When the adaptive filter is working, the error signal decreases in magnitude, and this slows down the movement of the coefficients. The filter is observed to converge to give a solution.

Adaptive filters are the digital filters with an impulse response, or transfer-function, which can be adjusted or changed over the time to match desired system characteristics. Unlike fixed filters, which have a fixed impulse response, adaptive filters do not require complete prior knowledge of the statistics of the signals to be filtered. Adaptive filters require little or no prior knowledge and have the capability of adaptively tracking the signal under non-stationary circumstances. For an adaptive filter operating in a stationary environment, the error-performance surface has a constant shape as well as orientation. When, however, the adaptive filter operates in a non-stationary environment, the bottom of the error-performance surface continually moves, while the orientation and curvature of the surface may be changing too. Therefore, when the inputs are non-stationary, the adaptive filter has the task of not only seeking the bottom of the error performance surface but also continually tracking it.

3.13 DIGITAL FILTER

The heart of the control system is a digital filter with specific properties, which synthesizes the anti-noise. FIR filters are one of two primary types of digital filters used in Digital Signal Processing (DSP) applications, the other type being IIR. The advantages of FIR filters outweigh the disadvantages, so they are used much more than IIR filter

3.14 INFINITE IMPULSE RESPONSE FILTER

IIR filters are one of two primary types of digital filters used in Digital Signal Processing (DSP) applications (the other type being FIR). IIR filters can achieve a given filtering characteristic using less memory and computations than a similar FIR filter. But as it has many disadvantages when compared with the FIR filter. They are more susceptible to problems of finite-length arithmetic, such as noise generated by computations, and limit cycles. They are more difficult (slower) to implement by means of fixed-point arithmetic. They do not provide the computational benefits of FIR filters for multiple-rate applications (decimation and interpolation). IIR filters are generally more difficult to deal with and analyze than FIR filters. IIR filters can be stable or unstable. It has feedback that might cause instability, but it doesn't always.

3.15 FINITE IMPULSE RESPONSE FILTER

- The controller filter may take many forms, the most common of which is the Finite Impulse Response (FIR) filter. FIR filter may be represented, as shown in Fig. 3.6. Here, z^{-1} represents a delay of one (input) sample and w_i represents filter weight i.
- FIR filters are ideally suited to tonal noise problems, i.e. noise with harmonics, where the reference signal is a few sinusoids and where the control signal does not in any way corrupt the reference signal.

When there are resonances in the system or if there is some noise feedback from the control source to the reference sensor, resulting in the corruption of the reference signal, the FIR filter is not the best choice. Then the Infinite Impulse Response (IIR) filter is often chosen for its ability to directly model the poles in the system resulting from such effects.

The main advantage of the IIR filter is that it uses fewer weight coefficients than required by the FIR filter for a complex system, thus reducing computational load, but there are possibility of instability, slower convergence and also the possibility of convergence to a local minimum in the error surface.

The three parameters that affect the performance of a digital filter in an ANC system are the type of filter, the filter weight values and the number of weights. The adaptation algorithm of the controller is responsible for tuning the adaptive filter so that the resulting control signal minimizes the error signal received by the controller. Various algorithms will be introduced depending upon if the noise in the environment is linearly varying or non-linearly varying.

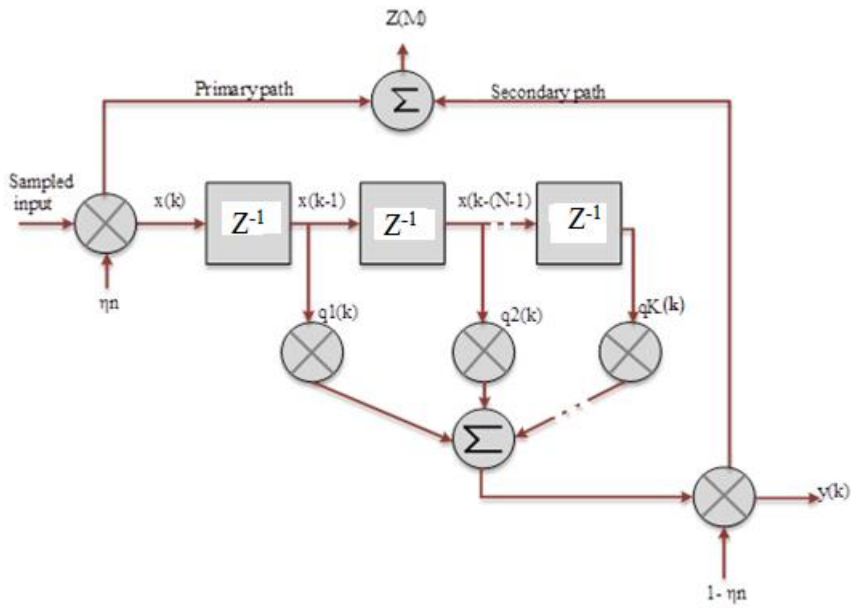


Figure 3.6: FIR filter architecture

Generally, the filters are used to remove noise from the signal. The low pass FIR filters are used to remove the high noise present in the signal. Similarly, high pass FIR filters are used to remove the low noise present in the signal. As part of the filtration process, the signals will be separated and restored. By the usage of multipliers, adders, and delays, the present output through this digital FIR filter can be implemented. Figure 3.6 shows the FIR filter architecture.

The filter design includes the selection of filter coefficients and filter length. The forward-path introduces the group delay or phase shift between the filter coefficient and the input signal. It is a discrete-time system. FIR filter has no feedback element and consumes fewer amounts of memory. It gives a linear phase output and contains only the zeroes. There are no poles in the system so that the location of zero does not affect the stability of the system.

Compared to IIR filters, FIR filters offer the following advantages:

- They can easily be designed to be a linear phase (and usually are). Linear-phase filters delay the input signal but don't distort its phase.
- They are simple to implement. On most DSP microprocessors, the FIR computation can be done by looping a single instruction.
- They are suited to multi-rate applications. By multi-rate, we mean either decimation (reducing the sampling rate), interpolation (increasing the sampling rate), or both. Whether decimating or interpolating, the use of FIR filters allows some of the computations to be omitted, thus providing an important computational efficiency. In contrast, if IIR filters are used, each output must be individually computed, even if that output will be discarded (so the feedback will be incorporated into the filter).
- They have desirable numeric properties. In practice, all DSP filters must be implemented using finite-precision arithmetic, that is, a limited number of bits. The use of finite-precision arithmetic in IIR filters can cause significant problems due to the use of feedback. Still, FIR filters without feedback can usually be implemented using fewer bits, and the designer has fewer practical problems to solve related to non-ideal arithmetic.
- They can be implemented using fractional arithmetic. Unlike IIR filters, it is always possible to implement FIR filter using coefficients with a magnitude of less than 1.0. (The overall gain of the FIR filter can be adjusted at its output if desired.) This is an important consideration when using fixed-point DSP because it makes the implementation much simpler.

3.16 METHODS TO IMPROVE STABILITY IN ANC SYSTEMS

The perturbation method of frequency domain time difference simultaneous perturbation (FDTDSP) has already been used to improve the stability and cancellation performance of the ANC system. This method does not know about the knowledge of the secondary path model, because it can track the system automatically. The conventional perturbation method due to the cancellation performance is degraded during the entire frequency band. The magnitude of the perturbation is fed to the controller over the time domain. In doing so, the proposed approach enhances the cancellation performance and stability of the system. Filter coefficients are updated using the FxLMS algorithm (Widrow and Stearns 1985).

The advantages of the (FxLMS) algorithm are,

- Simplicity
- Small computational complexity
- Easy to install in hardware

The above-mentioned algorithm has to be used to find the secondary source to avoid the noise from the primary side. If the secondary path changes, the system becomes unstable, and the error is also increased. Those problems are solved by the perturbation method, so there is no need for secondary path models. The gradient vector of the perturbation method is enhanced through the addition of the perturbation coefficients to the filter. This method is suitable for the multichannel system, in which the computational complexity is being reduced.

The noise sources obtained from the speakers, feedback controller, and the microphone, which is applied to the air-duct and the air-conditioning unit. According to the flow direction of the incoming sound, the speaker is positioned with respect to the microphone. The sound delay is the major issue owing to this when travelling over the distance at a particular time interval. High frequency oscillations are reduced, and the low frequencies are imported into the filter loop.

Many control strategies are designed by identifying the sound trajectory in the air duct, loop shaping, and feedback fed to the controllers. The sensitivity function of the controllers has been derived from these controllers, and it is stable for all frequencies.

Both controllers are created in such a way that the sensitivity function of the closed-loop system is stable for all frequencies. Overall stability is required, but the control applicability at certain frequencies is controlled with a very small gain for stability. To overcome this problem, a real-time Youla Updating controller is used to update the controller real-time. The shaping of the controller in real time, based on the minimization of the standard microphone output, will result in a better controller for unknown incoming sound. Especially for incoming sound with a few dominating frequencies, the result is much better. Finally, an active controller sound reduction can be achieved in the lower frequency range of $50 - 300\ Hz$.

In some application scenarios of feedforward ANC, the output of the secondary source is transmitted to the reference sensor. This contaminates the quality of the reference signal and deteriorates the stability and performance of the ANC system. Based on the concept of equivalent secondary path, the phase deviation between the equivalent secondary path and the real secondary path to analyze the convergence behaviour of the system with acoustic feedback has been used. If the phase deviation exceeds 90^0 at some frequencies, it is difficult to converge around those frequencies. The noise reduction performance decreases, and the system may become unstable. Experiments are carried out to evaluate the performances of these approaches for solving the acoustic feedback induced problems, which includes the method of using a unidirectional microphone, the method of using the Filtered-u LMS (FuLMS) algorithm, the feedback neutralization method and the online modelling method. Both experimental and simulation results show that all these approaches can improve the noise reduction performance and are effective when there is acoustic feedback in the feedforward ANC systems. Still, each approach has its advantages and disadvantages. The unidirectional method is the most convenient, but the directivity is poor in the low-frequency range. The FuLMS algorithm has a low computational load. However, convergence is a difficult issue. The feedback neutralization method has the best performance but has weak robustness when the system is time-varying. The online modelling method doesn't require an extra filter, but its performance is slightly worse than other solutions due to complicated adjustment parameters.

For communication headsets equipped with active noise reduction (ANR), the performance of the control system may influence the communication signal reaching the ear. Conversely, the communication signal may perturb the operation of the ANR system. The interaction between the communication and control signals depends primarily on the control structure, and the bandwidths and frequency responses of the signal channels. The effects are described for two circumaural communication headsets with similar passive, and active, noise reductions, one with an analog feedback control system and the other an adaptive digital feedforward control system. Measurements were conducted in a diffuse sound field, with the headsets mounted on a head and torso simulator. The frequency response of sound reproduced by the communication channel was measured when the ANR system was not operating, and when the control system was operating, with sweeping pure-tones, and broadband noise. The speech intelligibility was estimated for environmental noise shaped to represent the spectrum of speech, the noise within a tank, or the noise within an aircraft cockpit, by the Speech Transmission Index (STI). The STI and fidelity of sound reproduced by the communication channel of the device with a feed-forward control structure tended to exceed that of the more common feedback control structure. This appeared to be a consequence of the compromised frequency response of the earphone and drive electronics employed in the feedback control system to maintain the stability of the feedback loop, as well as the presence of communication sounds sensed by the control microphone that was fed back into the controller. The lack of corruption of the communication signal by the feed-forward control system, together with the possibility of using electro-acoustic components with flat frequency responses, suggests that this control structure may be more consistent with the audio fidelity requirements of advanced auditory communication systems.

Active sound profiling can be used for increasing the sound quality in a passenger car, for example, by modifying the engine noise inside the car cabin. A fundamental algorithm in active sound profiling is the command-FxLMS (C-FxLMS) algorithm, which is an extension of the famous FxLMS algorithm widely used in ANC. The computational demand of the C-FxLMS algorithm becomes excessive in multiple-channel systems with engine noise components to be controlled using several loudspeakers and microphones. The most time-consuming part of the C-FxLMS algorithm is the filtering of the reference signals. In order to reduce the computational burden, a new way to modify the reference signals in narrowband systems is developed. Instead of conventional filtering operations, this method is based on delaying the sinusoidal reference signals and modifying their amplitude. The algorithm should work reliably and maintain stability in all operating points. An adaptive leakage has been developed for the C-FxLMS algorithm to increase its robustness.

Research over the past decade has demonstrated a substantial increase in noise reduction performance for circumaural hearing protectors through feedforward active noise reduction (ANR) based on least mean square (LMS) methods. However, commercialization of feedforward ANR hearing protection devices has yet to occur. Specifically, the dynamic range of noise sources, the potential for leakage around circumaural earcups, vibration conditions of high noise environments, and the need for communication requires ANR algorithms that are robust to large variations in the acoustic dynamics of hearing protectors. To meet this need, a hybrid ANR architecture that exhibits excellent stability margins and performance for both stationary and non-stationary noise sources are presented. The hybrid system is comprised of a Lyapunov-tuned leaky LMS feedforward component and a broadband digital feedback ANR system. The contribution of each component to ANR performance is adjusted by individual feedforward and feedback gain factors, and stability margins are defined by the net increase in these gains that can be accommodated while maintaining the system stability. Stability and noise reduction performance of the hybrid system are validated experimentally using an earcup from a commercial circumaural hearing protector and using a prototype active earplug.

In some practical ANC applications, non-target noise (including intended signals such as speech and white noise for online modelling of the secondary path) often corrupts residual noise sensed by the error sensor. Non-target noise reduces the convergence rates of the ANC algorithm and online modelling of the secondary path. It even leads to the instability of the IMC-based feedback ANC in some cases. Hence, non-target noise must be considered in order to improve the convergence rate and system stability. The prediction error filter is utilized to improve the convergence rate in the online secondary - path modelling. Weight-constrained FxLMS algorithm and the weight averaged FxLMS algorithm are designed to improve the system stability and convergence rate, respectively. Cascading adaptive algorithm is there to remove non-target noise and improve the steady-state performance of ANC systems. A linear prediction filter is utilized to improve the system stability in the IMC-based feedback ANC system when broadband noise corrupts the error signal.

3.17 SUMMARY

This chapter presents the classification of ANC systems. It also describes the applications of the ANC system and the approaches for noise reduction. This chapter also presents the basic structure of the ANC scheme, adaptive control, different types of filters, existing optimization methods for the active noise reduction and the methods to improve the stability of the system. The ANC scheme based on the modified Filtered-s Least Mean Square (MFsLMS) algorithm is discussed in the next chapter.

CHAPTER 4

DESIGN OF ANC SYSTEM USING A MODIFIED FILTERED S LEAST MEAN SQUARE ALGORITHM FOR THE REDUCTION OF NOISE

The details of the ANC system have been discussed in Chapter 3. The different types of existing algorithms have also been discussed in Chapter 3. This chapter handles the Objective-1 of this thesis work. This chapter aims to discuss the design of the ANC system using Modified Filtered s Least Mean Square (MFsLMS) algorithm. The stability, as well as the performance of the designed system, has been discussed in Chapter 5.

4.1 DESIGN OF ANC BY MFsLMS ALGORITHM

From the mentioned procedures in section 3.7, the nonlinear segments of GFLANN algorithm and FsLMS algorithm will not perform well in mitigating the nonlinear segments of domestic voice due to several relationships attained in nonlinear controller coefficients. The modified FsLMS (MFsLMS) algorithm is presented to solve this kind of issues, which is shown in Fig. 4.1.

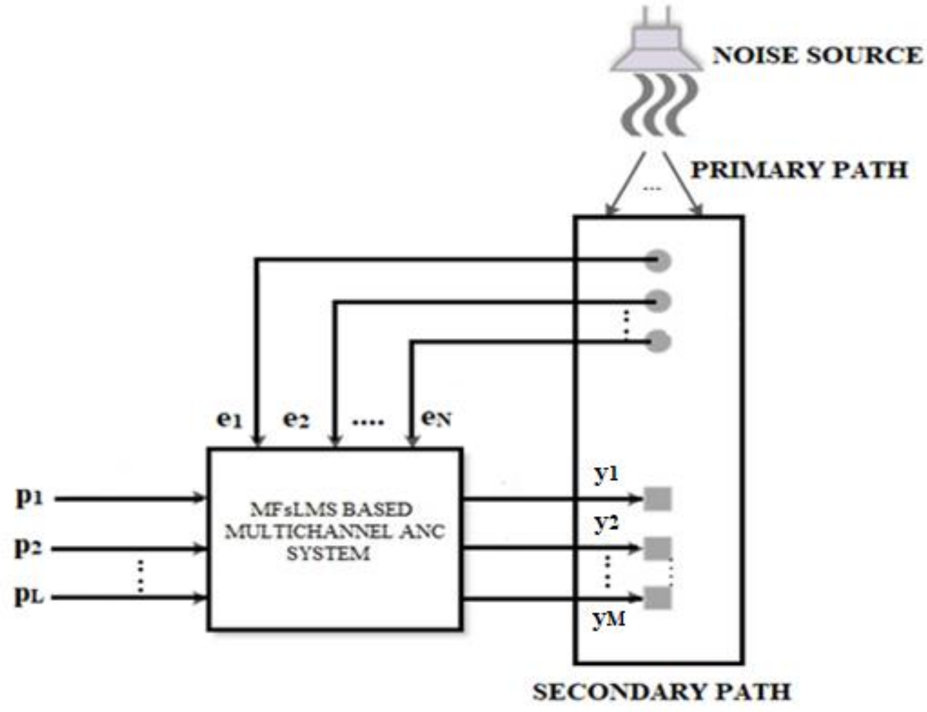


Figure 4.1: Schematic of MFsLMS based on multichannel ANC.

4.2 Analysis of MFsLMS algorithm

In Fig. 4.1, $p_1, p_2, \cdots\cdots, p_L$ are the reference microphones, $y_1, y_2, \cdots\cdots, y_M$ are the loudspeakers and $e_1, e_2, \cdots\cdots, e_N$ are the error microphones shown.

$p_l(n)$ is the signal used as input at the l-th reference microphone at the instant n; $1 < l < L$

$y(n)$ is defined as the output signal at the loudspeaker m at the instant n

$\boldsymbol{w}_{l,n}(\boldsymbol{n})$ is the adjustable weight vector, which connects l-th reference microphone to n-th error microphone

$\boldsymbol{s}_i(\boldsymbol{n})$ is the signal vector, which is functionally expansion of the input signal $p_l(n)$

$e(n)$ is the noise or the error signal sensed by the reference microphone

$d(n)$ is the primary noise signal at the n-th error microphone

$a(n)$ is the impulse response

The expression for error microphones is represented by Eq. (4.1).

$$e(n) = d(n) + a(n) * y(n) \tag{4.1}$$

The cost function is given by Eq. (4.2).

$$\xi = \sum_{n=1}^{N} e_n^2(n) \tag{4.2}$$

The output signal is expressed by Eq. (4.3).

$$y(n) = \sum_{l=1}^{L} \boldsymbol{w}_{l,n}(n) * \boldsymbol{s}_i(n) \tag{4.3}$$

Here '$*$' is the convolution operator. The expression of the modified weight vector is expressed by Eq. (4.4).

$$\boldsymbol{w}_{l,n}(n+1) = \boldsymbol{w}_{l,n}(n) - \frac{\mu}{2}\hat{\nabla}(n) \tag{4.4}$$

Here, μ is the stability factor denoting the convergence. If it holds a small value, it means enhanced stability but reduced convergence and vice-versa, $\hat{\nabla}$ is an estimation of the gradient of χ with respect to the weight vector $\boldsymbol{w}_{l,m}(n)$.

Functional expansion of $\boldsymbol{s}_i(n)$ is carried out with Maclaurin series. The series expansion, according to the modified algorithm, is given by Eq. (4.5).

$$\boldsymbol{s}_i(n)=\left\{\begin{array}{l} x_i(n),\frac{h}{1!}x_i^{'}(n),\frac{h^2}{2!}x_i^{''}(n),\ldots x_i(n-1),\frac{h}{1!}x_i^{'}(n-1), \\ \frac{h}{2!}x_i^{''}(n-1),\ldots x_i(n-m+1),\frac{h}{1!}x_i^{'}(n-m+1),\frac{h}{2!}x^{''}(n-m+1) \end{array}\right\} \tag{4.5}$$

The alteration will be in functional enlargement term that mitigates the computational complexity of the algorithm.

MFsLMS algorithm is developed for use in an ANC system for situations where a nonlinear reference noise process is to be mitigated with a non-minimum phase secondary path estimate. MFsLMS algorithm is used here to compute normalized mean square error (NMSE) value. In terms of NMSE, the proposed algorithm outperforms the standard FxLMS algorithm and even exhibits better performance than the VFxLMS algorithm. Additionally, it can be easily implemented to get the results.

This algorithm is suitable for the nonlinear structure of low noise removal. The convergence speed of the algorithm depends on the step size. If the convergence speed increases, the step size will decrease. FsLMS algorithm is very easy to implement. The number of operations is reduced as well as the primary noise is attenuated. This algorithm is enabled to compute the normalized mean square error at the low level, and it is represented by Eq. (4.6).

$$NMSE=10\log_{10}\left(\frac{E\left(e^2(n)\right)}{\sigma_d^2}\right) \tag{4.6}$$

Here, σ_d^2 is the variance of the primary noise at the cancellation point, $e^2(n)$ is the square of the error at n^{th} iteration and E*(.)*is the expectation operator.

4.3 Effectiveness of MFsLMS algorithm

In the derivation of the FsLMS algorithm, the M-element transformed vector s has been used instead of the N-element input signal vector x. Referring to Fig. 4.2, the following can be written.

H(z): The transfer function of the primary path from the reference microphone to the error microphone *d(n)*: The primary noise signal at the cancellation point

e(n): The residual noise sensed by the error microphone, which is expressed by Eq. (4.7)

$$e(n) = d(n) + a(n) * y(n) \tag{4.7}$$

In Eq. (4.7), *a(n)*, the impulse response of the secondary path is transfer function *A(z)* and '$*$' denotes convolution operation.

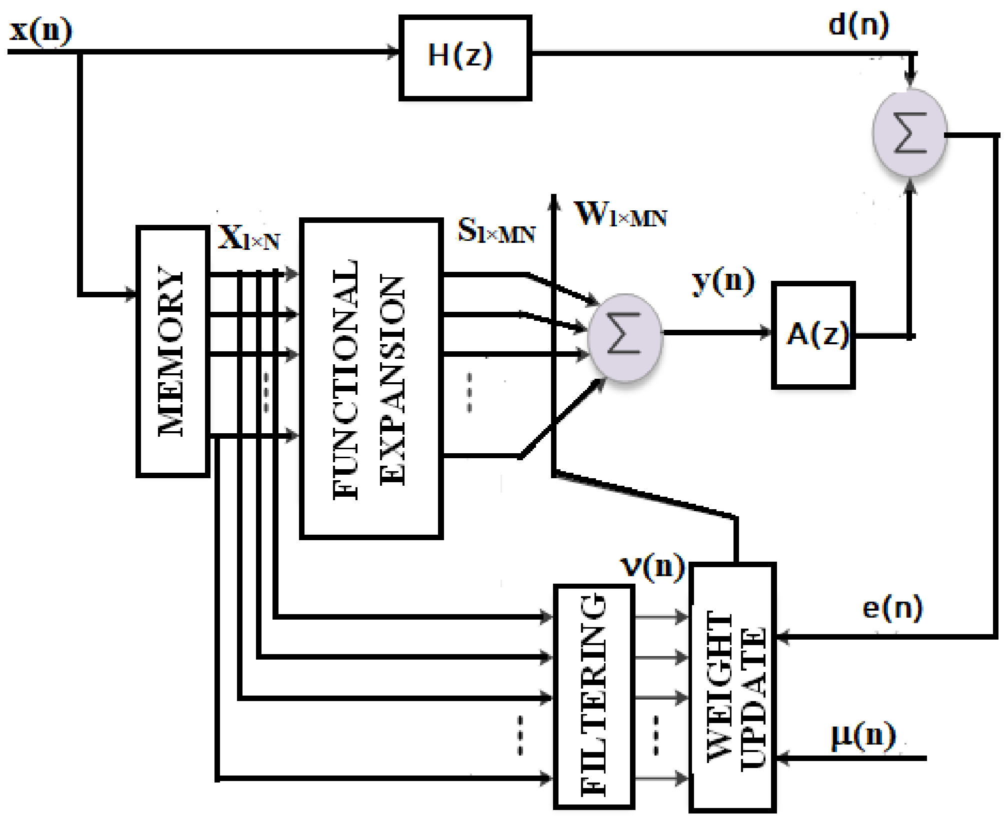


Figure 4.2: Block diagram of ANC with MFsLMS algorithm.

$\tilde{A}(z)$: The estimate of the secondary path.

$\boldsymbol{v}(n)$: The filtered vector in which each signal element is obtained by filtering the corresponding signal elements of ***s(n)*** with the secondary path estimate $\tilde{A}(z)$.

Hence Eq. (4.7) can be expressed by Eq. (4.8).

$$e(n) = d(n) + a(n) * \sum_{i=1}^{M} \boldsymbol{w}_i \boldsymbol{s}_i \tag{4.8}$$

In the Z-domain, Eq. (4.8) can be expressed by Eq. (4.9).

$$E(z) = D(z) + A(z)W(z)S(z) \tag{4.9}$$

Where *E(z), D(z), A(z), W(z), and S(z)* are the z-transforms of the residual noise *e(n)*, desired noise to be cancelled *d(n)*, secondary path impulse response *a(n)*, weight vector ***w(n)***, and functionally enhanced signal element vector ***s(n)***, respectively. Let the output be expressed by Eq. (4.10).

$$y(n) = \boldsymbol{w}^T(n)\boldsymbol{s}(n) \tag{4.10}$$

Where the functionally enhanced input vector *s(n)* and the corresponding adaptive coefficient (weight) vector *w(n)* at time index n is defined as $\boldsymbol{s} = \left[\boldsymbol{s}_1(n), \boldsymbol{s}_2(n), ..., \boldsymbol{s}_M(n)\right]^T$ and $\boldsymbol{w} = \left[\boldsymbol{w}_{1,}\boldsymbol{w}_2, ..., \boldsymbol{w}_M\right]^T$. In the Z-domain, (4.10) is expressed by Eq. (4.11).

$$Y(z) = W(z)S(z) \tag{4.11}$$

The length of ***s(n)*** and ***w(n)*** are both equal to *M = N(2P+1)*, where *N* is the number of the memory elements and *P* is the order of the functional expansion. The special case of *P=0* is a simple FIR filter, being *s(n) = x(n)* and *M = N*.

Eq. (4.8) is rewritten and expressed by Eq. (4.12) to derive MFsLMS algorithm.

$$e(n) = d(n) + a(n) * \left[\boldsymbol{w}^T(n)\boldsymbol{s}(n)\right] \tag{4.12}$$

The cost function (ξ) has already been expressed by Eq. (4.2).

The weight vector *w(n)* can be adjusted according to the following update equation, which minimizes the mean square error (MSE) as expressed by Eq. (4.13).

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) - \frac{\mu}{2}\hat{\nabla}(n) \tag{4.13}$$

Where $\hat{\nabla}(n)$ is an instantaneous estimate of the gradient of ξ for the weight vector ***w(n)*** as expressed by Eq. (4.14).

$$\hat{\nabla}(n) = \frac{\partial \xi}{\partial \boldsymbol{w}} = 2e(n)\frac{\partial y(n)}{\partial \boldsymbol{w}} = 2e(n)\left[\frac{\partial\left\{a(n) * \left[\boldsymbol{w}(n)\boldsymbol{s}(n)\right]\right\}}{\partial \boldsymbol{w}}\right]$$

$$\therefore \hat{\nabla}(n) = 2e(n)\left[\boldsymbol{s}(n) * a(n)\right] \tag{4.14}$$

Substituting the values $\hat{\nabla}(n)$ expressed by Eq. (4.14) in Eq. (4.13), Eq. (4.15) is obtained.

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) - \mu e(n)\left[\boldsymbol{s}(n) * a(n)\right] \tag{4.15}$$

Here μ denotes the step size, which controls the convergence speed of the MFsLMS algorithm. In practical ANC system, $\tilde{a}(n)$ is used as an estimate of *a(n)* and is obtained by linear modelling techniques. Thus, *a(n)* may be replaced by $\tilde{a}(n)$ in (4.15) and Eq. (4.16) is obtained.

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) - \mu e(n)\boldsymbol{v}(n) \tag{4.16}$$

Where $v(n)$ is expressed by Eq. (4.17).

$$\boldsymbol{v}(n) = \left[\boldsymbol{s}(n) * \tilde{a}(n)\right]. \tag{4.17}$$

4.4 COMPUTATIONAL COMPLEXITY

Computational complexity is an important issue when implementing the algorithm in real-time application. In feed-forward ANC structure, three stages of signal processing computation are performed. These stages of computation are

- Generating the control signal
- Filtering the reference signal through the estimated secondary path
- Updating the controller weights.

The computational complexity of the MFsLMS algorithm is computed with the proposed ANC system, with reference microphone (L= 1); loudspeaker (M = 2); error microphone (N = 4); memory size (m = 10); filters (n = 3); and order of expansion (P = 1), parameters (assumed). In the MFsLMS, there is no reason to evaluate the trigonometric terms. The multiplication and addition, of the proposed MFsLMS algorithm and available FsLMS algorithm, have been presented in Table 4.1. The original contribution of the proposed topology says that the reduction of computational complexity by the number of multiplication and the additional blocks are reduced when compared with the previous FsLMS algorithm. Thus, the computational complexity is reduced.

Table 4.1: Computational complexity.

Length of a secondary path (V)	FsLMS		MFsLMS	
	Multiplication	Addition	Multiplication	Addition
2	852	634	316	154
4	950	781	332	202
6	1024	948	348	250
8	1095	1012	364	298

By increasing the number of secondary paths, the multiplication and addition operations are counted. It is seen that with two secondary paths, MFsLMS algorithms have very less multiplication and addition operations compared with FsLMS method as the number of secondary paths increases the computational complexity of both algorithms increases. It is clear from Table 4.1 that with the increase in the number of secondary paths, FsLMS have very high computational complexity in terms of multiplication and addition. But for MFsLMS algorithm, the rate of increase of computational complexity is very low.

4.5 SUMMARY

The chapter presents the design of the ANC scheme by the modified algorithm. The ANC scheme of modified Filtered-s Least Mean Square (MFsLMS) algorithm is discussed, and design procedures are carried out in this chapter. The mathematical analysis of MFsLMS algorithm and its effectiveness is discussed in this chapter. The MFsLMS algorithm has been compared with the established FsLMS algorithm. The outcomes show that MFsLMS algorithm is computationally faster. The analysis of the stability of the ANC system and performance analysis of the ANC system by modified FsLMS and hybrid PSOFF algorithm of the ANC structure is discussed in the next chapter.

CHAPTER 5

STABILITY ENHANCEMENT AND PERFORMANCE ANALYSIS OF ANC SYSTEM BY MODIFIED FsLMS AND HYBRID PSOFF ALGORITHM

5.1 STABILITY OF ANC SYSTEMS

Performance problems of the ANC system are stability and convergence. These are solved by the adaptive algorithm based on MFLMS. Initially, the characteristic equations are derived, whose poles are identified in order to analyze the stability of the system. For the higher-order feedback ANC system, the roots are difficult to achieve. The acoustic path can lead to a higher delay than the electrical path, making the system as a higher order feature. Prior to this, stability was well defined by the frequency domain approach. The performance of the stability reflects the parameters of filter length, base frequency, and delay length. One of the most important technique for stability is Nyquist based on the frequency response.

5.2 STABILITY IMPROVEMENT OF ANC SYSTEM USING OPTIMIZATION

The stability analysis makes the major issue for the real-time ANC applications due to the feedback mechanism. The estimated model of the electro-acoustic coupling path is adopted to the feedback system, which is in the form of FIR filter. The secondary path is renamed by electro-acoustic coupling path. A few examples of the secondary path are analogue to the digital microphone, loudspeaker etc. The secondary model of the feedforward system is perfectly modelled to avoid the feedback structure of the ANC system. Where the results of the study can indicate perfect modelling of the secondary pathway which can make the stability of the ANC feedback structure of true instability problems.

The set of goals regarding the optimization problems are as follows,

- Find the independent variables
- Find the objective function
- Parameter changes regarding decision variables

The stability of the proposed system should be treated with the optimization methods mentioned in Chapter 3. This method is the hybrid combination of the two algorithms to make the heuristic approach. This specific algorithm makes it possible to identify the stability of the ANC system by the MFsLMS algorithm.

5.3 STABILITY OVER FEEDBACK ANC SYSTEMS

The stability issue caused by the secondary path modelling is to be given in this section. The design of the ANC filter includes the model of the reference signal, and the primary noise, which is similar to y(n), and r(n) respectively. The state of y(n) uses the model of the secondary path $\hat{D}(z)$. Here where the primary noise d(n) is suppressed due to the generation of the secondary noise *q(n)* from the loudspeaker. The error signal from the microphone is mentioned, similar to *e(n)*. The expression for the reference signal $\hat{p}(n)$ is expressed by Eq. (5.1).

$$\hat{p}(n)=\hat{q}(n)+e(n)=q(n)*\hat{d}(n)+e(n) \tag{5.1}$$

The transfer function of the feedback ANC system is defined by Eq. (5.2).

$$H(z)=\frac{M(z)}{N(z)}=\frac{1-W(z)\widehat{D}(z)}{1+W(z)[D(z)-\widehat{D}(z)]} \tag{5.2}$$

The correspondence of Eq. (5.2) is,

$W(z)$ is the adaptive filter with N-type

$D(z)$ is the secondary path error

$\hat{D}(z)$ is the estimated model of $D(z)$

$\hat{S}(z)$ is the internal estimated model of $S(z)$

If the Eq. (5.2) is without the error signal, $\hat{D}(z)$ is equal to the $D(z)$. Then from Eq. (5.2), Eq.(5.3) can be obtained.

$$H(z)[1]=1-W(z)\widehat{D}(z) \tag{5.3}$$

The adaptive feedback ANC system with the presence of zero but there are no poles, which guarantees the stability of the feedback system. The coefficient of the denominator function becomes higher-order, due to the error occurs in the estimated secondary path. This is because, the adaptive filter is higher-order and hence it creates much more delay to the secondary path $D(z)$, and the estimated path $\hat{D}(z)$.

The error of the delay component has to be established by the estimated model $\hat{D}(z)=z^{-\hat{\Delta}}$, and the secondary path model, $D(z)=z^{-\Delta}$ respectively. The adaptive filter model W(z) contains the secondary path and the primary path, and both are with the constant magnitude component.

The propagation time delay between the microphone and the speaker is denoted by Δ, this is ranged from hundreds of microseconds to tens of milliseconds, and then the delay can be expressed by Eq. (5.4).

$$H(z)=\frac{M(z)}{N(z)}=\frac{1-W(z)z^{-\hat{\Delta}}}{1+W(z)\left[z^{-\Delta}-z^{-\hat{\Delta}}\right]} \tag{5.4}$$

Equation (5.4) states that the delay model of the transfer function, which is obtained from Eq. (5.2). The stability of the closed-loop is derived in terms of the filter length, frequency, and secondary path delay. The phase and the magnitude response of the closed-loop transfer equation are given by Eq. (5.5).

$$h(e^{j\omega})=w(e^{j\omega})\ [e^{-j\omega\Delta}-e^{-j\omega\hat{\Delta}}] \tag{5.5}$$

Eq. (5.5) is the denominator of Eq. (5.4), in which the term of $z \longrightarrow e^{j\omega}$.

The polar plot of the open-loop frequency response never encloses the Nyquist plot, which is enclosed for all frequency at a point (-1, 0).

The alternative Nyquist criteria have to be derived for the stability criteria, in which the open-loop frequency is less than one when the frequency is to be $\omega=180^0$.

$\left\{At\ \ \omega=180^0\ then\ \ the\ open\ loop\ \ frequency\ is\ equals\ to\pm\pi\right\}$

The stability criteria have to be enhanced when the Eq. (5.6) is to be satisfied, for that take the modulus of Eq. (5.5).

$$\left|w(e^{j\omega})\right|.\ \left|e^{-j\omega\Delta}-e^{-j\omega\hat{\Delta}}\right|\omega=\omega_{180^0}<1.0\ , \tag{5.6}$$

In which the frequency point ω_{180^0} can be expressed by Eq. (5.7).

$$\angle w(e^{j\omega})\ [e^{-j\omega\Delta}-e^{-j\omega\hat{\Delta}}]_{\omega=\omega_{180^0}}=\pm\pi. \tag{5.7}$$

At the frequency point ω_{180^0}, the open-loop frequency response $w(e^{j\omega})\ [e^{-j\omega\Delta}-e^{-j\omega\hat{\Delta}}]$ is on the real-axis of z-plane at $\omega=180^0$.

The specific type of the primary noise in terms of the quadratic function, $\left|\omega(e^{j\omega})\right|$, and $\left|e^{-j\omega\Delta}-e^{-j\omega\hat{\Delta}}\right|$, is equal to one. The computation of the magnitude response is the product of the two linearized terms. The stability bounds are less than one when quadratic function becomes less than one.

5.4 OPTIMIZATION TECHNOLOGIES

A newly developed hybrid optimization technique is selected in this research work to improve the stability of noise regulation. Optimization means maximization or minimization of one or more functions with any possible constraints. The evolutionary algorithms are based on the selection of individuals from the population and regeneration of new individuals guided by previous fitter individuals. In general, if selection pressure is high (often called exploitation), the convergence of the algorithm is fast. However, one may end up with an inferior result. On the other hand, if selection pressure is low (also called exploration), one is likely to get a superior result though convergence is poor. Here, a kind of optimization is needed according to experience to decide the selection pressure and diversity in the population. Another interesting property is “no free lunch theorem”. As such, an algorithm cannot be superior to other algorithms in all types of cases. Therefore, for the problem class under consideration, it is necessary to know what algorithm is the best.

Particle swarm optimization algorithm: The Particle Swarm Optimization (PSO) algorithm is inspired by the social behaviour of a flock of migrating birds trying to reach an unknown destination. In PSO, each solution is a bird in the flock and is referred to as a particle. A particle is analogous to a chromosome in GAs. As opposed to GAs, the evolutionary process in the PSO does not create new birds from parent ones. Rather, the birds in the population only evolve their social behaviour and accordingly their movement towards a destination. Each bird looks in a specific direction. When they communicate to each other, they identify the bird that is in the best location. Accordingly, each bird speeds towards the best bird using a velocity that depends on its current position. Each bird, then investigates the search space from its new local position, and the process is repeated until the flock reaches the desired destination.

Particle swarm optimization is an exciting new methodology in evolutionary computation that is somewhat similar to a genetic algorithm in that the system is initialized with a population of random solutions. Unlike other algorithms, however, each potential solution (called a particle) is also assigned a randomized velocity and then flown through the problem hyperspace. Particle swarm optimization is extremely effective in solving a wide range of engineering problems. It is very simple to implement, and it solves problems very quickly. In a PSO system, the group is a community composed of all particles, and all particles fly around in a multidimensional search space. During the flight, each particle adjusts its position according to its own experience and the experience of neighbouring particles, making use of the best position encountered by itself and its neighbours. The swarm direction of each particle is defined by the set of particles neighbouring the particle and its historical experience.

Particle swarm optimization shares many similarities with evolutionary computation techniques in general and GAs in particular. All three techniques begin with a group of a randomly generated population, and all utilize a fitness value to evaluate the population. They all update the population and search for the optimum with random techniques. A large inertia weight facilitates global exploration (search in new areas), whereas a small one tends to assist local exploration. The main difference between the PSO approach compared to EC and GA is that PSO does not have genetic operators such as crossover and mutation. Particles update themselves with internal velocity. They also have a memory that is important to the algorithm. Compared with EC algorithms (such as evolutionary programming, evolutionary strategy, and genetic programming), the information-sharing mechanism in PSO is significantly different. In EC approaches, chromosomes share information. Thus, the whole population moves as one group toward an optimal area. In PSO, only the best particle gives out the information to others. It is a one-way information- sharing mechanism; the evolution only looks for the best solution. Compared with ECs, all the particles tend to converge to the best solution quickly, even in the local version in most cases. In comparison to GA, the advantages are that PSO is easy to implement, and there are few parameters to adjust.

The pseudocode of the PSO algorithm is given in Pseudocode 1 as follows:

Pseudocode 1

```
For each particle

{
   Initialize particle
}

Do until maximum iterations or minimum error criteria
  {
     For each particle
     {
      Computed Data fitness value
      If the fitness value is better than pBest
      {
         Set pBest = current fitness value
      }
      If pBest is better than gBest
      {
         Set gBest = pBest
      }
   }

   For each particle
```

```
  {
    Computed particle Velocity
    Use gBest and Velocity to update particle Data
  }
}
```

Figure 5.1 shows the flowchart for the PSO algorithm.

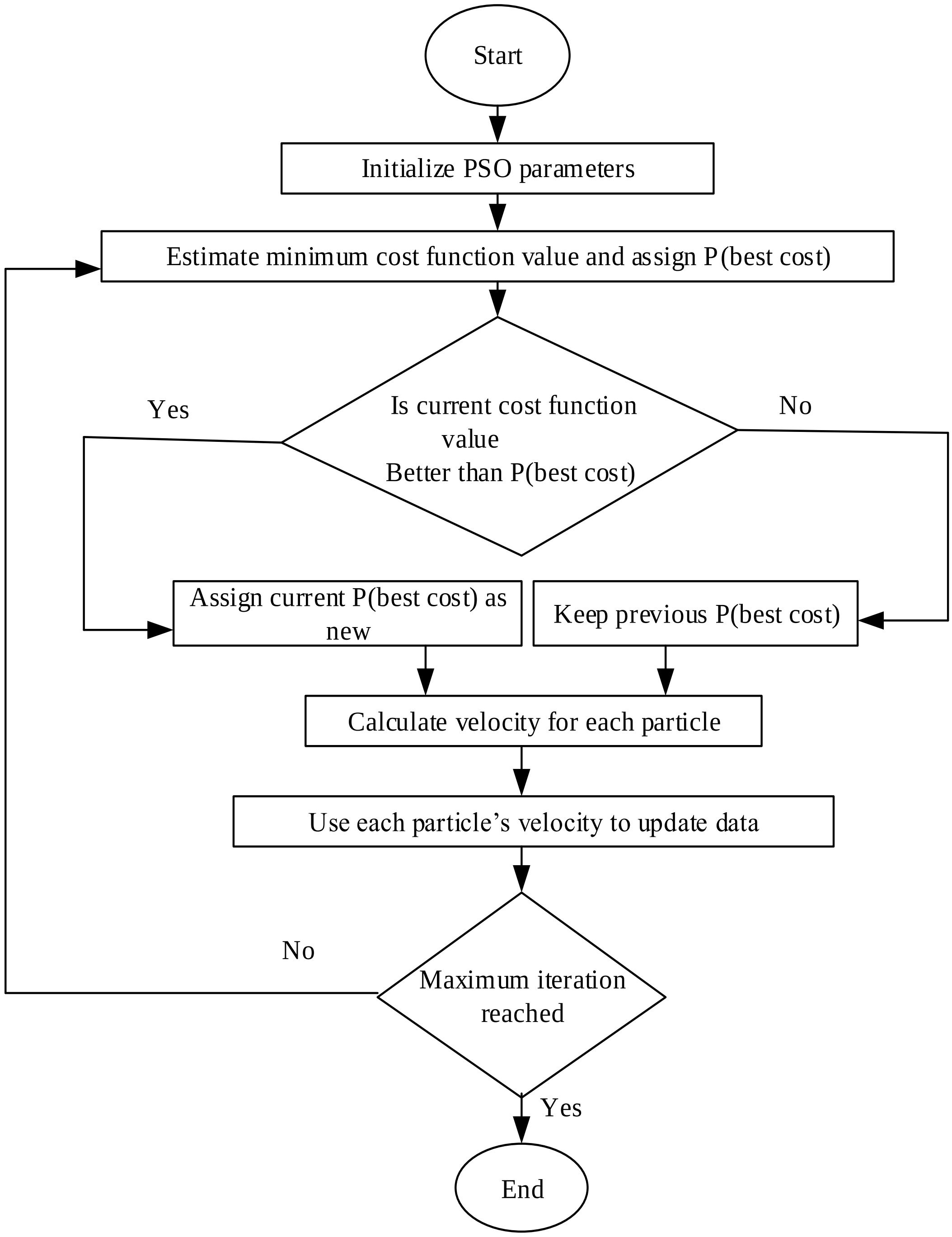


Figure 5.1: Flow chart for the PSO algorithm

Particle swarm adaptation has been shown to optimize a wide range of continuous functions successfully. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of individual vectors, called particles because they are conceptualized as moving points in multidimensional space. The individual particles are drawn stochastically toward the positions of their own previous best performance and the best previous performance of their neighbours.

Firefly algorithm: The Firefly (FF) Algorithm is a metaheuristic, nature-inspired optimization algorithm, which is based on the social flashing behaviour of fireflies. It is based on swarm behaviour such as fish, insects or bird schooling in nature. However, the firefly algorithm has many similarities with other algorithms which are based on the so-called swarm intelligence, such as the famous Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) optimization and Bacterial Foraging Algorithm (BFOA). FF algorithm is indeed much simpler both in concept and implementation. Its main advantage is that it uses mainly real random numbers, and it is based on global communication among the swarming particles called fireflies.

Biology-inspired metaheuristic algorithms have recently become the forefront of the current research as an efficient way to deal with many NP-hard combinatorial optimization problems and non-linear optimization constrained problems in general. These algorithms are based on a particularly successful mechanism of a biological phenomenon of Mother Nature in order to achieve optimization, such as the family of honey-bee algorithms, where the finding of an optimal solution is based on the foraging and storing the maximum amount of flowers' nectar. A new algorithm that belongs to this category of the so-called nature-inspired algorithms is the firefly algorithm, which is based on the flashing light of fireflies. However, the real purpose and the details of this complex biochemical process of producing this flashing light is still a debating issue in the scientific community. Many researchers believe that it helps fireflies for finding mates, protecting themselves from their predators and attracting their potential prey. In the firefly algorithm, the objective function of a given optimization problem is associated with this flashing light or light intensity, which helps the swarm of fireflies to move to brighter and more attractive locations in order to obtain efficient optimal solutions. Figure 5.2 shows the flow chart of the FF algorithm. The pseudocode of the FF algorithm is given in Pseudocode 2 as follows:

Pseudocode 2

Objective function $f(x)$, $x = (x_1, \ldots, x_d)^T$

Initialize a population of fireflies $x_i = (i = 1, 2, \ldots, n)$

Define light absorption coefficient γ

While (t < Max Generation)

for i=1: n all n fireflies

for j=1: n all n fireflies

Light intensity I_i at x_i is determined by $f(x_i)$

if $(I_j > I_i)$

Move firefly i towards j in all d dimensions

end if

Attractiveness varies with distance r via exp $[-\gamma r]$

Evaluate new solutions and update light intensity

end for j

end for i

Rank the fireflies and find the current best

end while

Postprocess results and visualization

5.5 HYBRIDIZATION APPROACHES

A hybridized PSO implementation integrates the inherent social, co-operative character of the algorithm with tested optimization strategies arising out of distinctly different traditional or evolutionary paradigms towards achieving the central goal of intelligent exploration. This is particularly helpful in offsetting weaknesses in the underlying algorithms and distributing the randomness in a guided way. PSO is a popular algorithm used extensively in continuous optimization. One of its well-known drawbacks is its propensity for premature convergence. Many techniques have been proposed for alleviating this problem. One of the alternative approaches is hybridization.

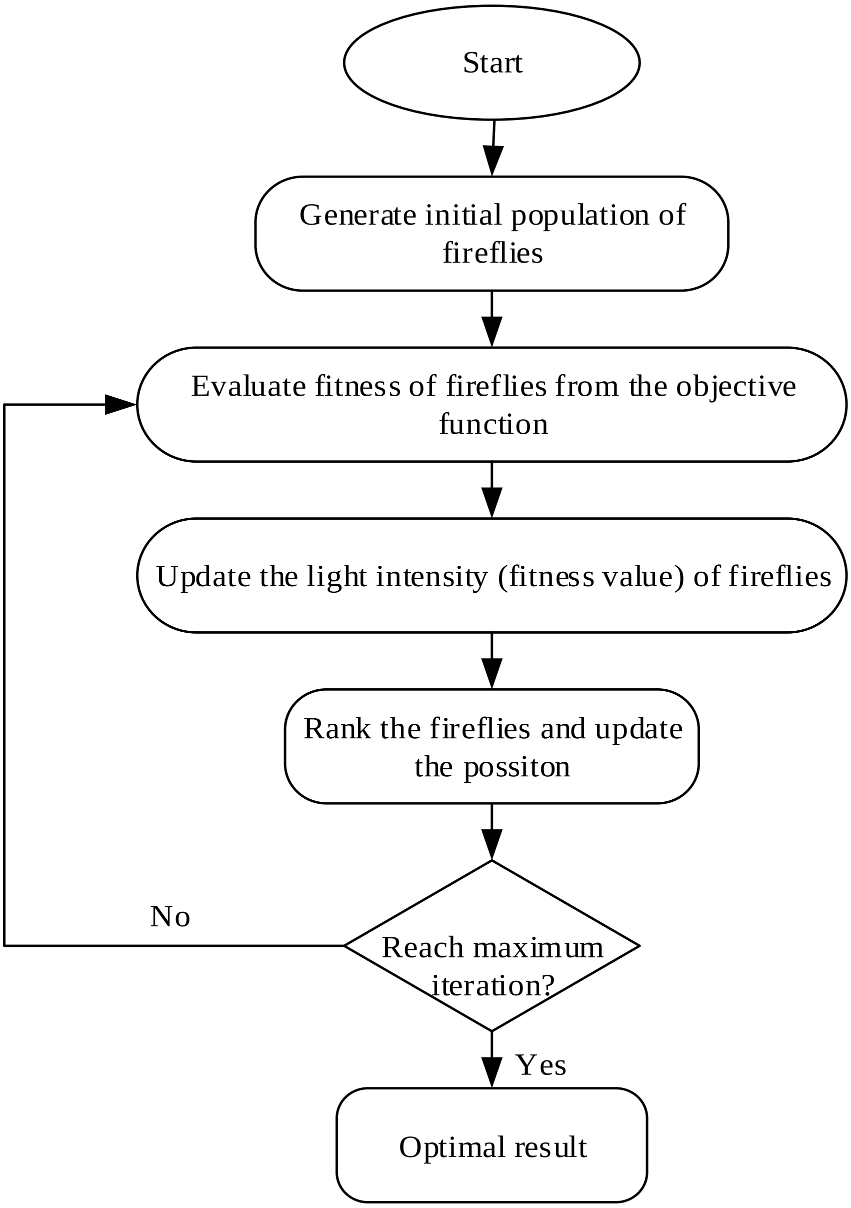


Figure 5.2: Flowchart of FF algorithm

5.5.1 HYBRID PSOFF ALGORITHM

To utilize different advantages of the PSO and FF algorithms, a hybrid form of these two known as HPSOFF has been created (Xia ***et al.***, 2017). During the optimization, the population is divided into two groups, and each chooses PSO or FF algorithm as their basic search technique for parallel executions. Apart from this, the information exchange about optimal solutions in case of stagnation, a knowledge-based detection operator and a local search for the tradeoff between exploration and exploitation as well as the employment of a BFGS Quasi-Newton method to enhance the exploitation led to several important observations. For instance, the exchange of optimal solutions led to an enriched and diverse population, and the inclusion of the detection operator and local search was justifiable for multimodal optimization problems where refinement of solution quality was necessary. The HPSOFF algorithm is a method of combining the advantages of faster computation of PSO algorithm with the robustness of the FF algorithm to increase the global search capability. The PSO algorithm starts with a set of solutions and based upon the survival of the fittest principle, and only the best solution moves from one phase to another. This process is repeated until any of the convergence criteria is met. At the end of the iterations, the optimal solution is one with the minimum total cost out of the set of solutions. The time of convergence of the PSO algorithm depends upon the values of the random set control parameters. The FF algorithm starts with an initial business solution, and each iteration enhances the solution until the convergence criteria are met. The optimal solution obtained from FF algorithm depends upon the quality of the initial solution provided. In the present document, the initial solution provided for the FF algorithm is the optimal solution obtained from the PSO algorithm. Since a best initial solution from the PSO algorithm is given to FF algorithm the optimal solution obtained from this Hybrid approach is better than the solution obtained from PSO or FF algorithms (Arunachalam ***et al.***, 2014).

In FF algorithm, the movement of an individual only depends on all other brighter individuals. Thus, the historical knowledge of the individual does not affect its current search behavior. In this case, while the brightest individual is located in a local optimum. The population is easily trapped into premature convergence. However, this search behavior causes FF algorithm to have promising ability on unimodal problems and simple multimodal problems.

In contrast with FF algorithm, the PSO algorithm selects much historical knowledge of particles to guide them to search for promising regions. Thus, the PSO algorithm has a more explorative capability, which is more suitable for complicated problems than FF algorithm. FF algorithm and PSO algorithm have their own merits. Integration of FF and PSO algorithms with a proper mechanism can design an outstanding hybrid optimizer.

Recently, hybridizing local search strategies with PSO and FF algorithms have attracted more attention. The simulation results verify the promising comprehensive performance, including faster convergence speed and higher solution quality, of the hybrid algorithms.

During the process of optimization, an entire population is divided into two parallel evolutionary sub-populations named as Pop_f and Pop_p, which choose FF and PSO as the basic algorithm, respectively. The two subpopulations exchange their own best solutions under certain conditions to share valuable knowledge. Specifically, if the best solution BestF in Pop_f consecutively stagnates more than a predefined generation Stagsub, it will be replaced by the best solution BestP in Pop_p while BestP is better than BestF, and vice versa. The details of exchanging elite knowledge are described below in Pseudocode 3.

Pseudocode 3

Begin

If $(Stag_f > Stag_{sub})\&\&(fit(BestF) > fit(BestP))$ **Then**

BestF=BestP;

$fit(BestF) = fit(BestP)$**;**

$Stag_f = 0$ **;**

Else if $(Stag_p > Stag_{sub})\&\&(fit(BestP) > fit(BestF))$ **Then**

BestP = BestF;

$fit(BestP) = fit(BestF)$;

$Stag_p = 0$**;**

End if

End

Pseudocode for a hybrid algorithm based on FF and PSO is as given Pseudocode 4:

Pseudocode 4

Initializing a population with N individuals;

Dividing the population into two sub populations: Pop_f and Pop_p ;

Initializing parameters: MaxFEs, T, $Stag_{sub}, Stag_{Pop}$;

Evaluating each xf_i and xp_i which are individuals in Pop_f and Pop_p , respectively;

$fes = N, t = 1, Stag_f = 0, Stag_p = 0, Stag_g = 0$;

Updating BestF, BestP and GBest;

While (fes <MaxFEs&&t<T)

t=t+1;

Updating individuals in Pop_f according to it; Updating fes ;

$If\left(fit(xf_{best}) < fit(BestF)Then\right)/^{*}\ xf_{best}$ is the current best individuals in Pop_f */

BestF = xf_{best} ; fit (BestF)= fit (xf_{best});

$Stag_f = 0;$ /* $Stag_f$ is the stagnation generations of firefly population*/

Else $Stag_f = Stag_f + 1$;

End if

Updating individuals in Pop_p ; Updating fes ;

$If\left(fit(xP_{best}) < fit(BestP)Then\right)/^{*}\ xP_{best}$ is the current best individual in Pop_p */

BestP = xP_{best} ; fit (BestP) = fit (xp_{best});

$Stag\ p = 0;$ /* $Stag_p$ is the stagnation generations of firefly population*/

Else $Stagp = Stag_p + 1$;

End if

Tmpx= $\{X \mid fit(X) = \min\left(fit(BestF), fit(BestP)\right)\}$;

If $\left(fit(Tmpx) < fit(GBest)\right)$ Then

GBest=Tmpx; $fit(GBest = fit(Tmpx))$;

$Stag_g = 0$; /* $Stag_g$ is the stagnation generations of the whole population*/

Else $Stag_g = Stag_g + 1$;

End if

Exchanging elite individuals between two populations according to algorithm 1;

Carrying out the detecting operator according to algorithm 2;

Carrying out the local-searching operator according to algorithm 3;

End while

End

Figure 5.3 shows the flowchart of the HPSOFF algorithm.

5.4.2 STABILITY IMPROVEMENT OF ANC WITH HPSOFF ALGORITHM

Stability of an ANC system can be upgraded by the help of the proposed methodology. Here PSO algorithm is hybridized with the FF algorithm to enhance the stability of the system. FF algorithm is incorporated to update the position of particles. This is achieved with the movement of fireflies.

The fitness function is given by Eq. (5.8).

$$F = \frac{1}{\left[5 \times \left(2M+1\right) \times P_r\right]} \tag{5.8}$$

Where M is the number of the error microphones M = 4

P_r is the probability of the error noise (0.2)

The movement of fireflies is demonstrated by Eq. (5.9).

$$Z_{ii} = Z_{ii-1} + D_{new} e^{-\gamma r^2} + \alpha\varepsilon \tag{5.9}$$

Here γ : Light absorption coefficient (holds the value 1), r: the relative distance of fireflies, α is the randomization parameter (α =0.2), ε is a random number between 0 and 1 (ε = 0.1).

5.6 PERFORMANCE ANALYSIS BY MFsLMS AND HYBRID PSOFF ALGORITHM

The ANC system used for implementation and result generation is of the multichannel type with F reference microphones, P loudspeakers and M error microphones. A modified filtered algorithm is used to reduce noise. In this work, a modified filtered-s LMS algorithm is used for noise cancellation. Stability improvement is designed using a hybrid optimization called

HPSOFF algorithm, where PSO and FF are the two superior algorithms. Modification of the algorithm is done by using a Maclaurin series part. The modified algorithm can reduce computational complexity.

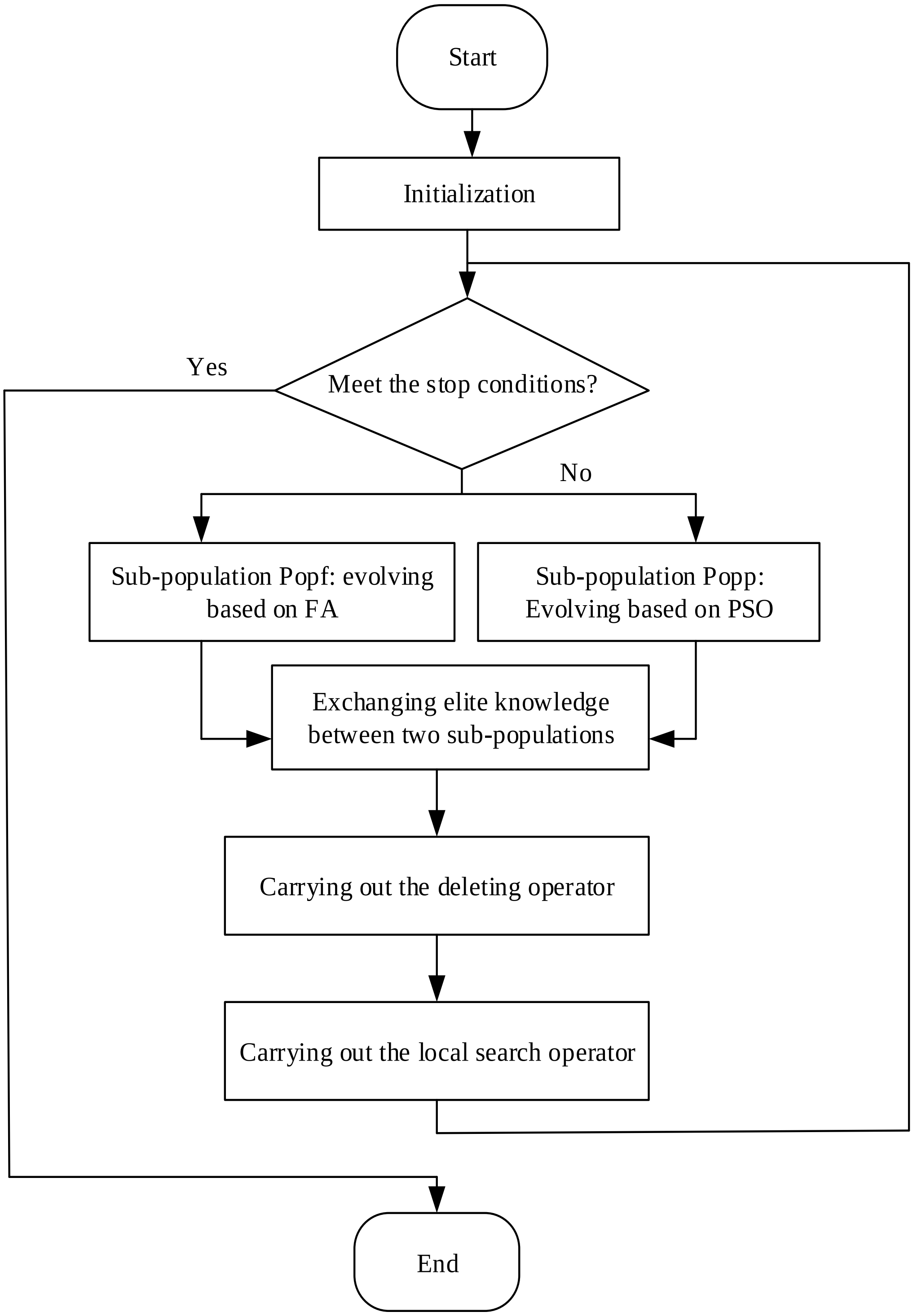


Figure 5.3: Flowchart of HPSOFF

The trigonometric expansion was the functional expansion used by the previously defined algorithms. Maclaurin series is an advanced computerized method with reduced complexity. MFsLMS algorithm gives better outcomes compared to FsLMS algorithm. The computer simulations are used to analyze the strength of the defined work with two different noise signals. The normalized mean square error (NMSE) value is plotted with the number of iterations for the performance evaluation. The successive relations are used for evaluating the values of the NMSE given by Eq. (5.10).

$$NMSE = 10\log_{10}\left(\frac{E(e^2(n))}{\sigma_d^2}\right) \tag{5.10}$$

In Eq. (5.10), σ_d^2 is the variance of the noise (at cancellation point) and $e^2(n)$ is the square value of the error function.

The performance of the system is studied with the normalized mean square error for two different types of noises. The proposed method has also been compared with the existing algorithms for the same purpose. The two signals used for analysis are logistic chaotic primary noise signal and a Gaussian noise signal.

5.6.1 CHAOTIC NOISE SIGNAL

Recently, chaotic signal processing has received much interest. Some signals, like radar sea clutter, speech, and indoor multipath effects, are better represented by deterministic chaotic rather than stochastic process. Understanding the chaotic process is useful in applications such as radar surveillance, secure communication, and narrowband interference cancellation in a chaotic spread-spectrum system. The main characteristic of a deterministically chaotic system is the sensitive dependence on initial conditions. Small differences in the initial input conditions can grow into large changes in the output value. Moreover, it is very difficult to predict the next system state, even if an accurate measurement of the current state can be obtained.

In the ANC system, the noise that is generated from a dynamic system may be nonlinear and deterministic chaotic rather than stochastic, white, or tonal noise processes. Research has shown that the noise measured from a ventilation fan exhibits chaotic behaviour. Three kinds of chaotic noises in the form of Logistic, Lorenz, and Duffing noise filters have been applied to test the capability of a proposed single channel nonlinear controller. The results from this study show that if the input signal is non-Gaussian and predictable, the use of a combination of linear and nonlinear controller produces better results than a linear one exclusively.

Among these chaotic noises, the Logistic type is the simplest and the most useful test signal, and it can be described as a second-order white and predictable nonlinear process. Chaotic logistic noise provides a simple and helpful test signal since it is a non-linear process of predictable second order.

x(n) is a zero-mean version of logistic noise generated by the recursive equation as given by Eq. (5.11).

$$x(n+1) = \lambda x(n)\ \left[1 - x(n)\right]. \tag{5.11}$$

From Eq. (5.11), the following Correlation of discrete-time with continuous-time signal as given by Eq. (5.12).

$$x(n) = x(t)_{t=nT_S}$$

i.e., $$x(t) = x(n)_{n=\frac{t}{T_S}}$$

i.e., $$x(n+1) = \lambda x(n)[1 - x(n)]$$

i.e., $$x\left(\frac{t}{T_s}+1\right) = \lambda x\left(\frac{t}{T_s}+1\right)\left[1 - x\left(\frac{t}{T_s}+1\right)\right]$$

i.e., $$x\left(\frac{t+T_s}{T_s}\right) = \lambda x\left(\frac{t+T_s}{T_s}\right)\left[1 - x\left[\frac{t+T_s}{T_s}\right]\right]$$

(5.12)

In Eq. (5.12) T_s denotes the sampling time.

5.6.2 GAUSSIAN NOISE SIGNAL

Gaussian noise is a statistical noise having probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian distributed. The probability density function p of a Gaussian random variable z is given by Eq. (5.13).

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \tag{5.13}$$

In Eq. (5.13) z, μ and σ represent the grey level, the mean value and the standard deviation respectively.

A particular case is white Gaussian noise, in which the values to any time pair are identically distributed and independent (and therefore uncorrelated). In communication channel testing and modelling, Gaussian noise is used as additive white noise to generate additive white Gaussian noise. In telecommunications and computer networking, communication channels can be affected by wideband Gaussian noise coming from many natural sources, such as thermal vibrations of atoms in conductors (referred to as thermal noise or Johnson-Nyquist noise), shot noise, black body radiation from the earth and other warm objects, and from celestial sources such as the sun.

5.6.3 SIMULATIONS USING LOGISTIC CHAOTIC NOISE

A logistic chaotic primary noise signal is generated by using a recursive Eq. (5.14).

$$x(n+1) = \lambda x(n)\ \left[1 - x(n)\right] \tag{5.14}$$

In Eq. (5.14) x(n) is a zero-mean version of logistic noise generated by the recursive equation. In this equation $\lambda = 0.01$ and x(0) = 0.9. Figure 5.4 denotes the noise signal for the considered chaotic noise. The non-linear noise is normalized to a signal value of one given below.

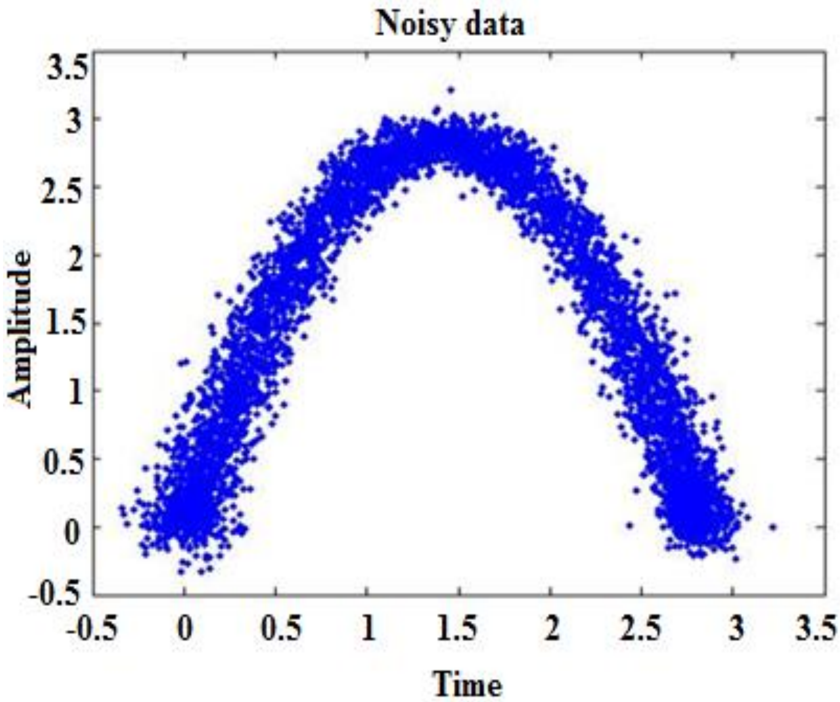


Figure 5.4: Chaotic noise signal

The primary and secondary path transfer functions used in the simulation are

$$H_{(1,1)}(z) = z^{-5} - 0.3z^{-6} + 0.2z^{-7},$$

$$H_{(1,2)}(z) = z^{-5} - 0.2z^{-6} + 0.1z^{-7},$$

$$H_{(1,3)}(z) = z^{-5} - 0.3z^{-6} + 0.1z^{-7},$$

$$H_{(1,4)}(z) = z^{-5} - 0.2z^{-6} + 0.2z^{-7},$$

$$A_{(1,1)}(z) = z^{-2} - 1.5z^{-3} + 0.2z^{-4},$$

$$A_{(1,2)}(z) = z^{-2} - 1.7z^{-3} - z^{-4},$$

$$A_{(1,3)}(z) = z^{-2} - 1.8z^{-3} - z^{-4},$$

$$A_{(1,4)}(z) = z^{-2} + 1.9z^{-3} - z^{-4},$$

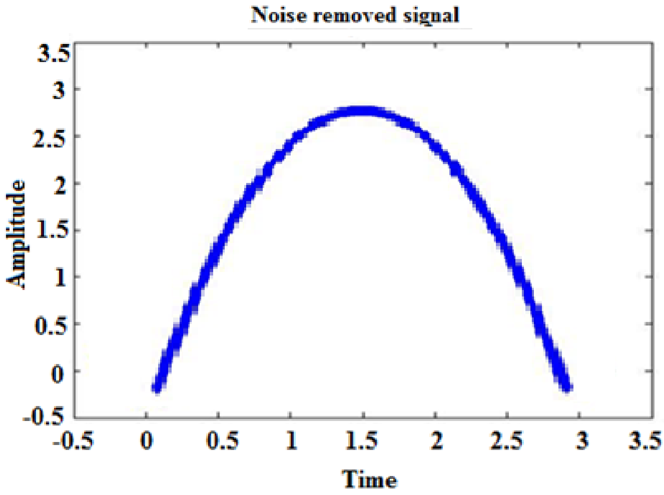
$$A_{(2,1)}(z) = z^{-2} + 1.5z^{-3} - z^{-4},$$

$$A_{(2,2)}(z) = z^{-2} + 1.2z^{-3} + 0.2z^{-4},$$

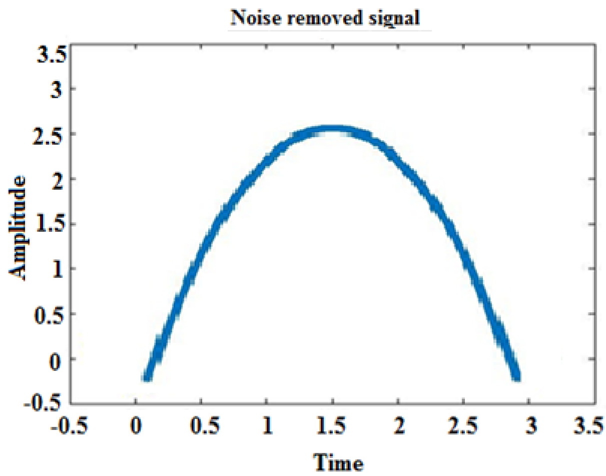
$$A_{(2,3)}(z) = z^{-2} + 1.1z^{-3} - z^{-4},$$

$$A_{(2,4)}(z) = z^{-2} + z^{-3} - z^{-4}.$$

The noise removed from the particular noise signal is shown in Fig. 5.5. Comparison carried out between the proposed methodology of noise cancellation and existing methods. From the two graphs, it is understood that the proposed method shows good performance than existing ones. A perfect signal is got from the noise signal after the implementation of the proposed method in the chaotic signal. From both graphs, the noise level is high with existing methods, and the noise level is highly reduced in the case of the proposed method. The noise cancellation performance yields a reduced normalized mean square error value. Figure 5.5 (a) and Fig. 5.5(b) are the expected outcome of the noise removed signal of the proposed method and existing method, respectively.



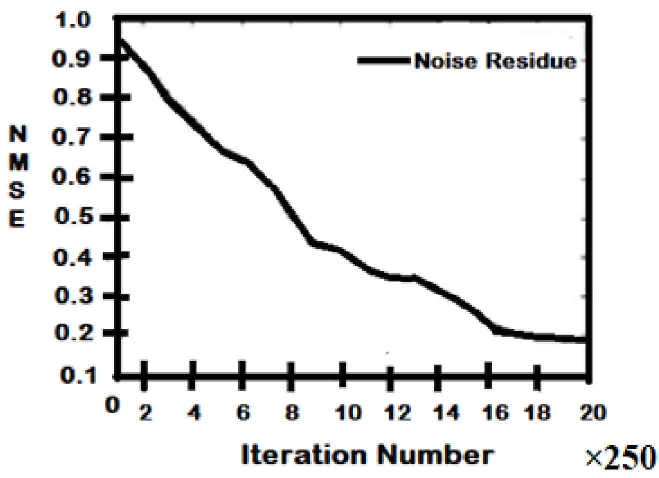
(a) Proposed method (MFsLMS)



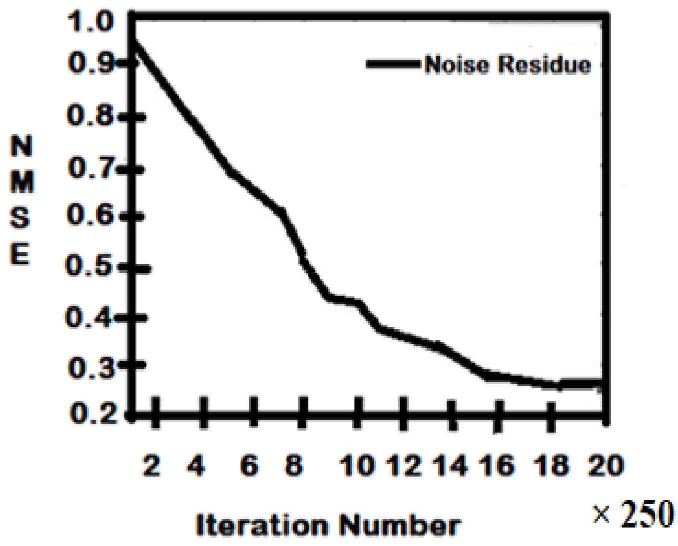
(b) Existing method (FsLMS)

Figure 5.5: Noise removed signals

Simulation parameters chosen are reference microphone (L= 1); loudspeaker (M = 2); error microphone (N = 4); and, the memory size, m = 10. The step size or learning rate used for FsLMS algorithm is $\mu = 0.1$ and that for MFsLMS algorithm $\mu = 0.000097$. Error cancellation performance of the proposed and existing methods using NMSE are shown in Fig. 5.6. A number of iterations used are 20×250=5000. NMSE is varying after each iteration. The minimum value of the normalized mean square error, for the proposed work, is 0.187 dB. When it is compared with conventional noise reduction techniques, the proposed work provides significant noise reduction. The minimum value of the normalized mean square error, of the existing technique, is 0.257 dB.



(a) Proposed method (MFsLMS)



(b) Existing method (FsLMS)

Figure 5.6: Number of iterations versus normalized mean square error

The proposed method has reduced NMSE value. Convergence and NMSE are approximately inversely proportional as the NMSE decreases the convergence speed increases. Optimal outputs are obtained with reduced computational time using the proposed method.

5.5.4 SIMULATIONS USING GAUSSIAN NOISE

The simulations have been carried out by assuming that the primary path exhibits nonlinear behaviour. The primary noise is generated at the cancelling point based on the following third-order polynomial model as given by Eq. (5.15).

$$d(n) = y(n-2) + 0.08y^2(n-2) - 0.04y^3(n-1) \tag{5.15}$$

In Eq. (5.16) y(n) is obtained from the following linear convolution as given in Eq. (5.15).

$$y(n) = x(n) * d(n) \tag{5.16}$$

In Eq. (5.16) *d(n)* is the impulse response of the path and the z-transform of *d(n)* is represented by *D(z)* is shown in Eq. (5.17).

$$D(z) = z^{-3} - 0.3z^{-4} + 0.2z^{-5} \tag{5.17}$$

In Eq. (5.16) x(n) is the reference noise. It is a sinusoidal noise defined as in case 1. For the comparison of the performance, the existing method FsLMS and the proposed modified technique are considered.

For comparison purpose, the tonal noise is generated by Eq. (5.18).

$$x(n) = \sin\left(\frac{2\pi f_n}{f_s}\right) \tag{5.18}$$

The results are plotted with the comparison of iteration and the normalized mean square error. The parameters for Case 2 were taken as in Case 1. The Gaussian input noise is given in Fig. 5.7.

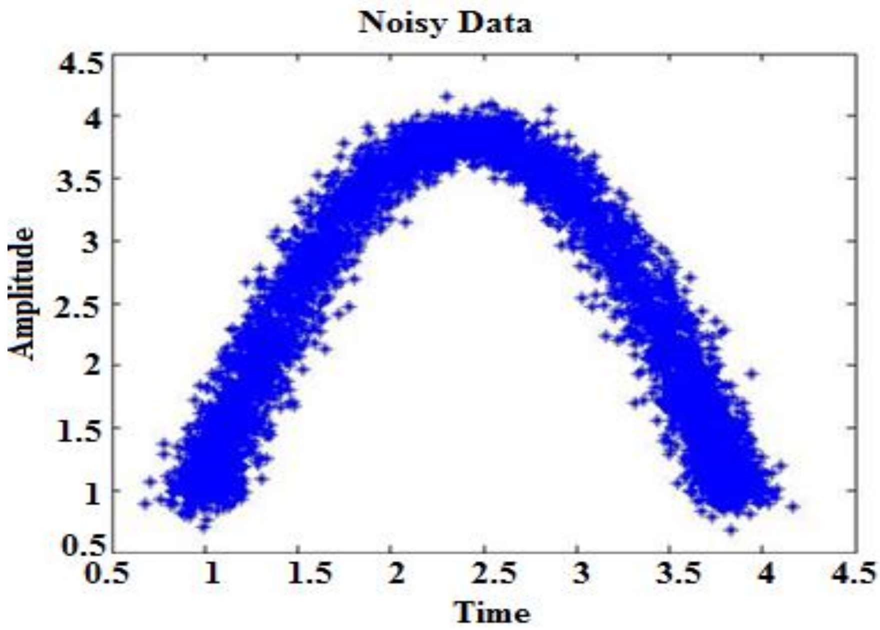
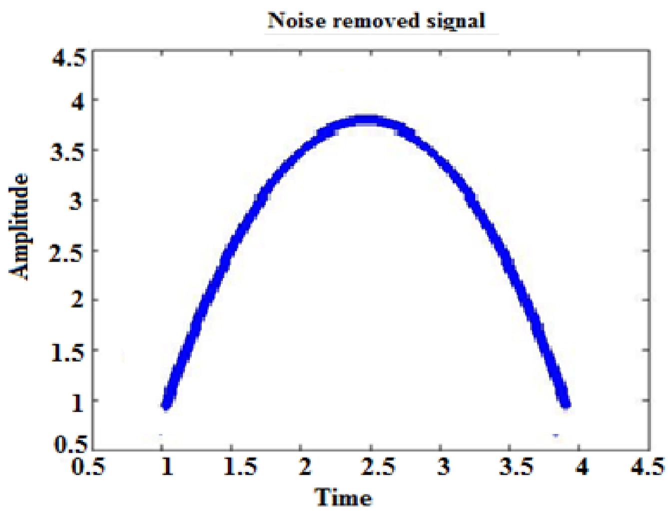
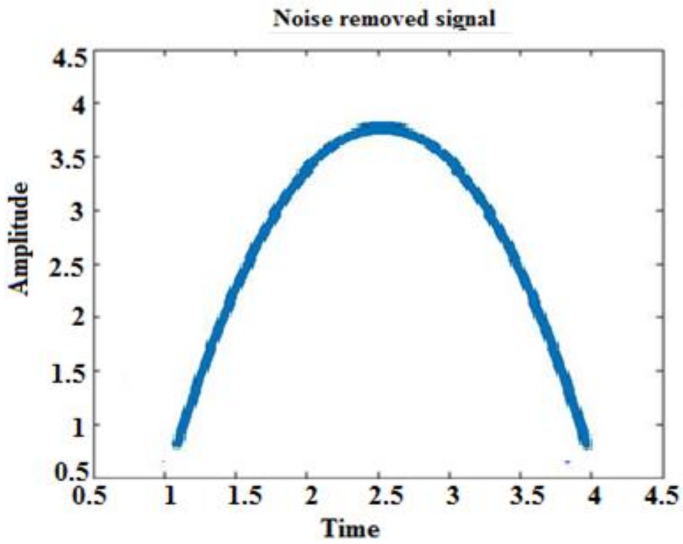


Figure 5.7: Gaussian noise signal

Figure 5.8 (a) and Fig. 5.8 (b) show the noised removed signal graph for the proposed method and the existing FsLMS method, respectively. Noise removed signal obtained using the proposed methodology is clearer than that obtained from an existing method.



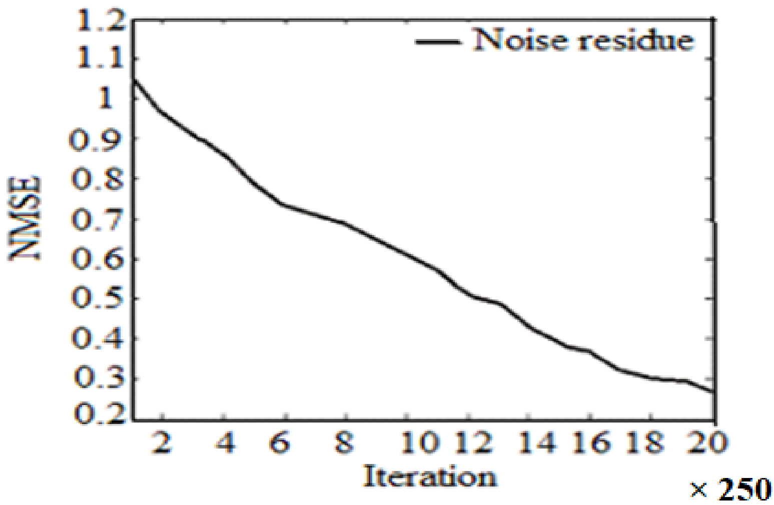
(a) Proposed method (MFsLMS)



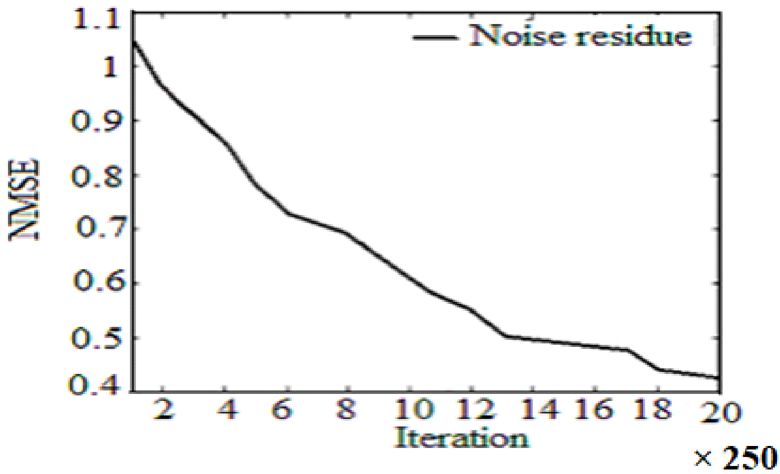
(b) Existing method (FsLMS)

Figure 5.8: Noise removed signal

The normalized mean square error is used for the comparison of defined work with the existing FsLMS algorithm. The mean square error obtained by the proposed and the existing methods have been shown in Fig. 5.9 (a) and Fig. 5.9 (b) respectively. From the result, it is evident that the MFsLMS algorithm dictates the ultimate noise removal in the signal. The minimum value of NMSE (dB) in the proposed case is 0.265 dB and for the existing case is 0.425 dB.



(a) Proposed method (MFsLMS)



(b) Existing method (FsLMS)

Figure 5.9: Number of iterations versus normalized mean square error (NMSE).

Table 5.1 shows the comparison of the proposed method with hybrid PSO-ABC (Particle Swarm Optimization-Artificial Bee Colony) and hybrid PSO-GA (Particle Swarm Optimization-Genetic Algorithm). The NMSE value (in dB) has been reduced by 0.187 dB with the time consumption of about 0.385 sec in the proposed method for Chaotic noise signal.

Table 5.1: Comparison of the proposed method with other hybrid algorithms for Chaotic noise signal

S.no	Method	NMSE (dB)	Computational time (sec)
1	MFsLMS+ PSO+FF	0.187	0.385
2	MFsLMS +PSO+ABC	0.300	0.524
3	MFsLMS +PSO+GA	0.428	0.628

Figure 5.10 clearly shows that the system with the proposed hybrid PSO-FF algorithm provides comparatively less NMSE value and computational time with existing methods like PSO-ABC and PSO-GA algorithms for Chaotic noise signal.

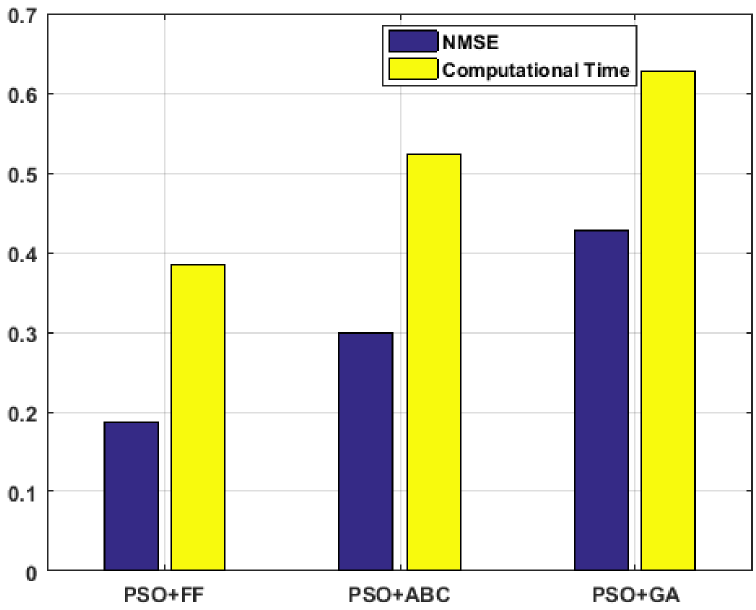


Figure 5.10: Comparison of HPSOFF with hybrid algorithms for the case of Chaotic noise signal

Table 5.2 shows the comparison of the proposed method with hybrid PSO-ABC (Particle Swarm Optimization-Artificial Bee Colony) and hybrid PSO-GA (Particle Swarm Optimization-Genetic Algorithm). The NMSE value (in dB) is reduced to 0.265 dB with the time consumption of about 0.412 sec in the proposed method for Chaotic noise signal.

Table 5.2: Comparison of the proposed method with other hybrid algorithms for Gaussian noise signal

S.no	Method	NMSE (dB)	Computational time (sec)
1	MFsLMS+ PSO+FF	0.265	0.412
2	MFsLMS +PSO+ABC	0.327	0.572
3	MFsLMS +PSO+GA	0.459	0.654

Figure 5.11 shows that the system with the proposed hybrid PSO-FF algorithm provides comparatively less NMSE value and computational time with existing methods like PSO-ABC and PSO-GA algorithms for Gaussian noise signal.

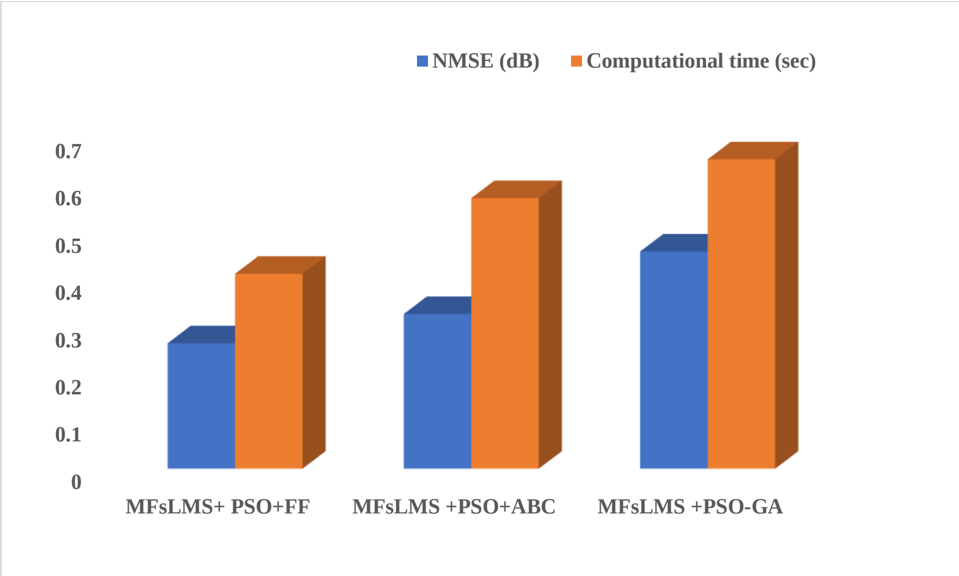
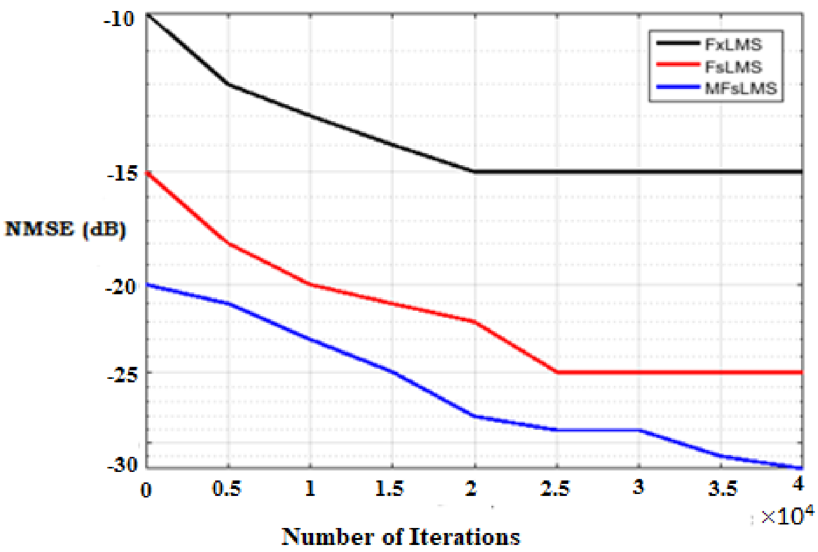
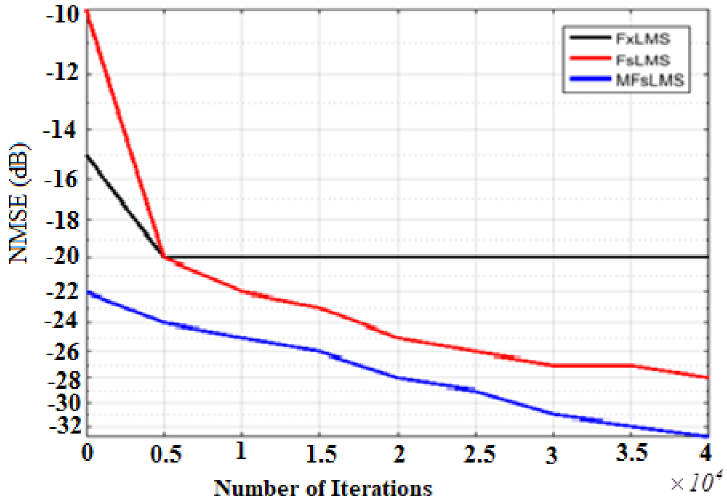


Figure 5.11: Comparison of HPSOFF with hybrid algorithms for the case of Gaussian noise signal

Figure 5.12 (a) and Fig. 5.12 (b) show the performance of the proposed MFsLMS algorithm with the existing FxLMS and FsLMS algorithms regarding the NMSE (in dB) vs iteration numbers (samples) for Chaotic noise signal and Gaussian Noise signal respectively.



(a) Chaotic noise signal



(b) Gaussian noise signal

Figure 5.12: Performance evaluation of the proposed method in terms of normalized mean square error (NMSE).

Figure 5.12 shows two comparisons of the graphs between NMSE(dB) Vs number of iterations using FxLMS, FsLMS and MFsLMS algorithms. For Chaotic noise signal proposed method to possess a very high negative value of NMSE. That means compared to the other two methods, this method is efficient. For a Gaussian noise signal, the suggested method has a very less value of NMSE. In effect, the stability and at the time convergence has been improved.

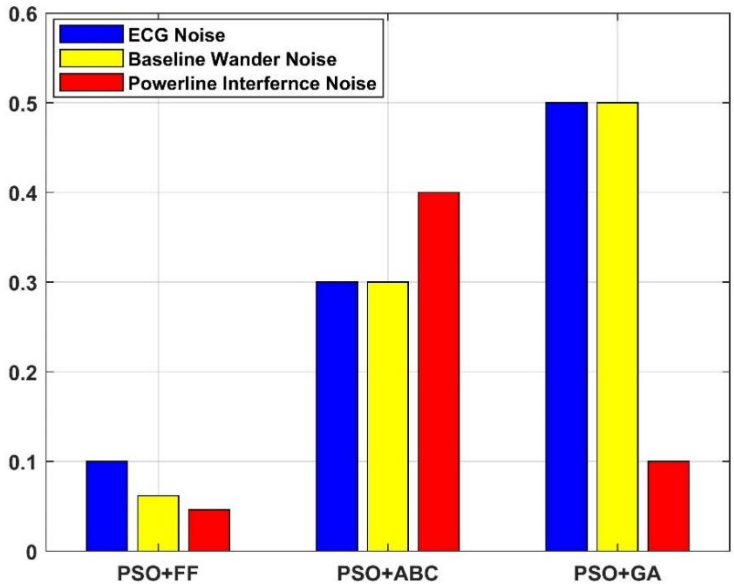


Figure 5.13: NMSE performance due to the influence of different noises

The performances are evaluated for the NMSE for different noises. Here PSO+FF performances are compared with PSO+ABC and PSO+GA algorithms as shown in Fig. 5.13. These algorithmic evaluations are performed for the three types of noises. The hybrid PSO-FF algorithm given better results compared to hybrid PSO-ABC and PSO-GA algorithms.

5.7 SIMULATIONS USING LOGISTIC CHAOTIC NOISY SIGNAL WITH NOISE REDUCING WITH TIME

The noisy signal is generated by scattering the pure signal datapoints with a monotonically decreasing variance. To generate the pure signal, datapoints has been generated using a recursive equation. Then the points are plotted against themselves with single point shift (First point to second last point as X axis, second point to last point as Y axis). Thereafter, each X value is passed through a sigmoid function given by (5.19).

$$y_1 = \frac{1}{1 + a \times e^{(-x\_val)}} \tag{5.19}$$

The sigmoid function scales the x values in such a way that the larger the x value is, the more it gets scaled down, that way, when input values keep on getting larger, the scaled values keep getting smaller, then, that scaled value is used to generate a uniformly distributed random number as given by Eq. (5.20).

$$y_2 = uniform\_random\left(-b \times y1 \; to \; b \times y1\right) \tag{5.20}$$

Using Eq. (5.19) and Eq. (5.20) , a noisy chaotic signal with noise reducing with time is generated from Eq. (5.14) and given in Fig. 5.14 using the proposed method as the proposed method gives better noise reduction. The signal after removing the noise is given in Figure 5.15.

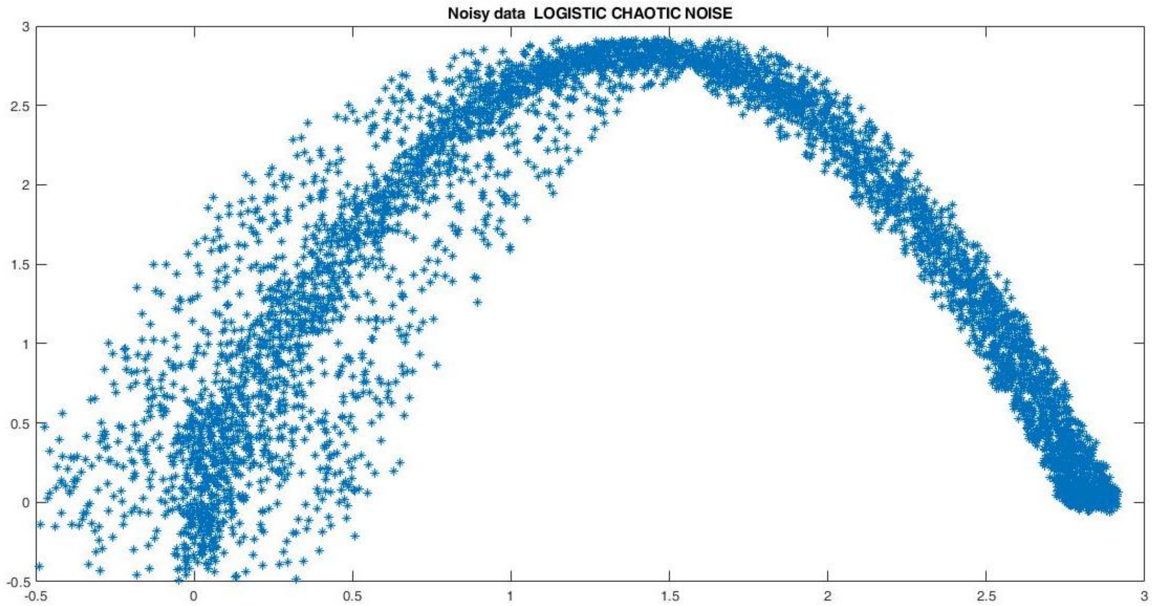


Figure 5.14: Noisy chaotic signal with noise reducing with time

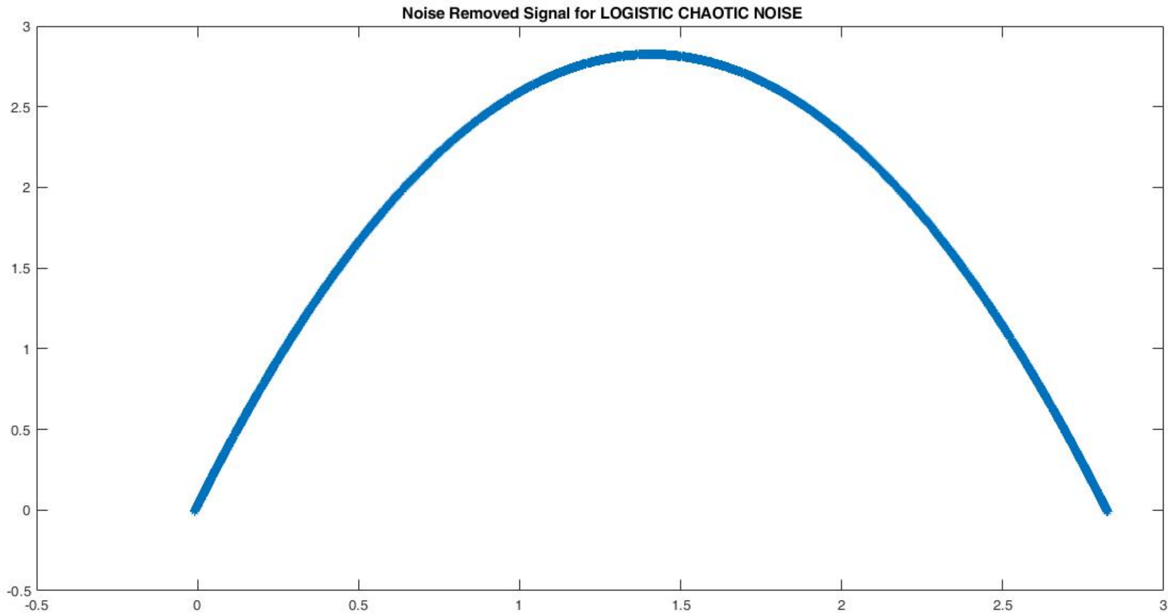


Figure 5.15: Noise removed chaotic signal obtained from Fig. 5.14

Table 5.3 shows the comparison of the proposed method with hybrid PSO-ABC (Particle Swarm Optimization-Artificial Bee Colony) and hybrid PSO-GA (Particle Swarm Optimization-Genetic Algorithm). The NMSE value (in dB) has been reduced by 0.187 dB with the time consumption of about 0.385 sec in the proposed method for noisy chaotic signal with noise reducing with time.

Table 5.3: Comparison of the proposed method with other hybrid algorithms for noisy chaotic signal with noise reducing with time

S.no	Method	NMSE (dB)	Computational time (sec)
1	MFsLMS+ PSO+FF	0.167	0.315
2	MFsLMS +PSO+ABC	0.334	0.454
3	MFsLMS +PSO+GA	0.378	0.548

5.8 SUMMARY

This chapter presents the stability enhancement of the ANC system using the optimization algorithms. This chapter also describes the optimization techniques such as particle swarm optimization (PSO) and firefly algorithm (FF). The hybridized optimization approach using the PSO algorithm and FF algorithm named as hybrid particle swarm optimization and firefly algorithm (HPSOFF) is also presented in this chapter. The pseudocode and flowchart of these algorithms are also described. This chapter presents the stability improvement of the ANC system with HPSOFF algorithm. The performance analysis of the ANC system using modified FsLMS and hybrid PSOFF algorithm is carried out in this chapter using two different noise signals. The chaotic and gaussian noise signals are used for simulation purpose. The stability of the ANC system is improved by the comparison of normalized mean square error (NMSE) with the proposed method and the other hybridized algorithms. The convergence of the ANC system is also improved in terms of computational time is presented. The proposed method has also been implemented to a chaotic noisy signal with noise reducing with time.

CHAPTER 6

DESIGN OF ANC SYSTEM USING HYBRID FLANN AND FIR FILTERS FOR THE EFFECTIVE DIMINUTION OF NOISE

6.1 FUNCTIONAL LINK ARTIFICIAL NEURAL NETWORK

The functional link artificial neural network (FLANN) (Kadam and Fatima, 2012) is a useful alternative to the multilayer artificial neural network (MLANN) (Pao ***et al.***, 1989). It has the advantage of involving less computational complexity and a simple structure for hardware implementation (Patra ***et al.***, 1999). The basic principle, the characteristic feature, and the mathematical treatment of FLANN are discussed next. The conventional MLANN (Rumelhart ***et al.***, 1986) involves linear links. An alternative approach is also possible, where the concept of functional link is used, which acts on an element of a model or on the whole of the model itself and generates a series of linearly independent functions. By this process, no new adhoc information is inserted into the process, but the representation gets enhanced. The functional link approach simplifies the learning algorithms and unifies the architecture for all types of nets. The new net is capable of accommodating three tasks: supervised learning, associative storage and recall, and unsupervised learning.

In the functional link model, an element x_k $1 \le k \le N$ is expanded to $f_1(x_k)$, $1 \le l \le M$. Various types of functional expansion models are possible. Three representative examples are power series expansion, trigonometry expansion, and tensor or outer product. In the power series expansion model, an element $x_k, 1 \le k \le N,$, is enhanced to $x_k^l ; 1 \le l \le R,$ with a constraint $|x_k| < 1$. In the case of a trigonometric expansion of order P, each input element x_k is mapped to $\left\{x_{k,\sin(i\pi x_k),\cos(i\pi x_k)}\right\}, 1 \le i \le P$. In the tensor model, a set of inputs $\{x_i\}$ is mapped as $\{x_i\} \Rightarrow \left\{x_{i,x_i x_j}\right\}, j > i \Rightarrow \left\{x_i, x_i x_j, x_i x_j x_k\right\}, k > j > i$ with $|x_i|, |x_j|,$ and $|x(k)<1|$. In this model, the total number of expanded components depends upon the number of input elements. Let us consider the problem of learning with a flat network, which is a network with no hidden layers. Let **X** be the Q input patterns each with N elements. The network configuration has one output. For the q^{th} pattern, the input components are $x_i^{(q)}, 1 \le i \le N$, and the corresponding output is $y^{(q)}$. The connecting weights are $w_i, 1 \le i \le N$, and the threshold is denoted by α . Thus $y^{(q)}$ is given by Eq. (6.1).

$$y^q = \sum_{i=1}^{N} x_i^q w_i + \alpha \qquad q = 1, 2, ..., Q \tag{6.1}$$

Eq.(6.2) is obtained by arranging all Q patterns.

$$\begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(q)} \\ \vdots \\ y^{(Q)} \end{bmatrix} = \begin{bmatrix} x_1^{(1)} & \cdots & x_N^{(1)} & 1 \\ x_1^{(2)} & \cdots & x_N^{(2)} & 1 \\ \vdots & \ddots & & \vdots \\ x_1^{(q)} & \cdots & x_N^{(q)} & 1 \\ \vdots & \ddots & & 1 \\ x_1^{(Q)} & \cdots & x_N^{(Q)} & 1 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_i \\ \vdots \\ w_N \\ \alpha \end{bmatrix} \tag{6.2}$$

Or in matrix form, Eq. (6.2) can be expressed by Eq. (6.3).

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{w} \tag{6.3}$$

The dimension of **X** is $Q\times (N+1)$.

If Q = N + 1 and *Det(**X**)* $\neq 0$, then Eq. (6.4) is obtained.

$$\boldsymbol{w} = \boldsymbol{X}^{-1}\boldsymbol{y}. \tag{6.4}$$

Thus, finding the weights for a flat net consists of solving a system of simultaneous linear equations for the weights **w.**

If $Q < (N+1)$,***X*** can be partitioned into a functional matrix $\boldsymbol{X_F}$ of dimension $Q\times Q$. By setting $\boldsymbol{w}_{Q+1} = \boldsymbol{w}_{Q+2} = ... = \boldsymbol{w}_{N=\alpha=0}$, and since $Det(\boldsymbol{X_F}) \neq 0$, w may be expressed by Eq. (6.5).

$$\boldsymbol{w} = \boldsymbol{X}_F^{-1}\boldsymbol{y}. \tag{6.5}$$

This will give only one solution. But if the matrix **X** is not partitioned explicitly, Eq. (6.5) yields only one solution, all of which satisfies the given constraints.

If $Q > (N+1)$, then Eq. (6.6) is obtained.

$$\boldsymbol{S}\boldsymbol{w}_F = \boldsymbol{y} \tag{6.6}$$

In Eq. (6.6) $\boldsymbol{S}, \boldsymbol{w}_F, \boldsymbol{y}$ are of dimensions $Q \times (N+1), (N+1) \times 1$ and $Q \times 1$, respectively.

$$\boldsymbol{w}_F = \boldsymbol{S}^{-1}\boldsymbol{y}. \tag{6.7}$$

Equation (6.7) is an exact flat net solution. However, if M > Q, the solution is similar to that of Figure 6.1. This analysis indicates that the functional expansion model always yields a flat net solution if a sufficient number of additional functions is used in the expansion.

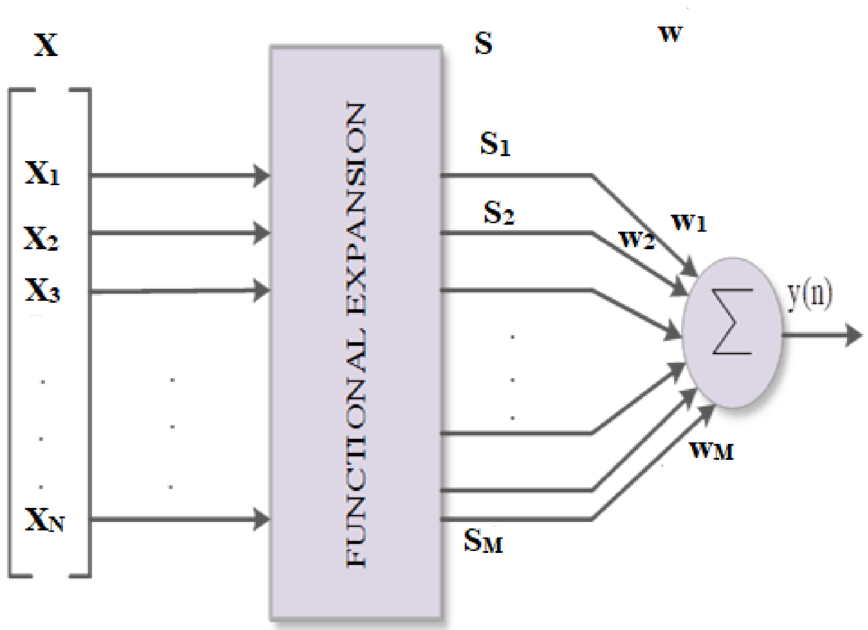


Figure 6.1: Structure of FLANN

Figure 6.1 represents a simple FLANN structure, which is essentially a flat net with no hidden layer. In FLANN, inputs are fed to the functional expansion block to generate functionally expanded signals, which are linearly combined with an element weight vector to generate a single output. Here, the trigonometric functional expansion is chosen for the FLANN structure because of the below-mentioned reason.

Basis of using trigonometric functional expansion

From Eq. (6.8) it may be seen that the condition for the existence of a weight solution depends on the existence of inverse of the matrix **S**. This is true only if the matrix equation is linearly independent, and may be achieved by the use of suitable orthogonal polynomials for the functional expansion. Some representative examples are Legendre, Chebyshev, and trigonometric polynomials. Of all the polynomials of p^{th} order with respect to an orthogonal system, the best approximation in the metric space is given by the p^{th} partial sum of its Fourier series with respect to the system. Therefore, the trigonometric polynomial basis functions given by Eq. (6.8).

$$\boldsymbol{s} = \{x, \sin(\pi x), \cos(\pi x), \sin(2\pi x), \cos(2\pi x), ..., \sin(P\pi x), \cos(P\pi x)\} \tag{6.8}$$

A compact representation of the function in the mean square sense. If P is the order of functional expansion, M = N (2P + 1), where N and M are the lengths of the input vector **s**. Here, **s** represents a column vector of the matrix **S**.

Trigonometric functional expansion-based ANC system

The FLANN employing trigonometric functional expansion with finite memory N and a finite order P can be described by the following input-output relationship given by Eq. (6.9).

$$y(n) = \sum_{i=1}^{M} w_i s_i \tag{6.9}$$

Where M = N (2P + 1).

Equation (6.10) gives the expression of s_i.

$$s_i = FE(x_k), \qquad \text{For } 1 \le i \le M, \quad 1 \le k \le N \tag{6.10}$$

And $FE(.)$ stands for functional expansion. In vector form, (6.9) is represented by Eq. (6.11).

$$y(n) = \boldsymbol{w}^T \boldsymbol{s} \tag{6.11}$$

Where s and w are presented by Eq.(6.12) and Eq.(6.13), respectively.

$$\begin{aligned} \boldsymbol{s} = \big[& s_{1,1}, s_{1,2}, s_{1,3}, ..., s_{1,2P+1}, s_{2,1}, s_{2,2}, s_{2,3}, ..., \\ & s_{2,2P+1}, ..., s_{N,1}, s_{N,2}, s_{N,3}, ..., s_{N,2P+1} \big]^T \end{aligned} \tag{6.12}$$

$$\boldsymbol{w} = [w_1, w_2, w_3, ..., w_M]^T \tag{6.13}$$

And $[.]^T$ denotes transpose of a matrix.

In general, the signal elements of s can be described by Eq. (6.14).

$$s_{i,j} = \begin{cases} x_i, & j = 1 \\ \sin(l\pi x_i), & j > 1, \quad j \text{ is even} \\ \cos(l\pi x_i), & j > 1, \quad j \text{ is odd} \end{cases} \tag{6.14}$$

Where $1 \le l \le P$. Denoting x as a vector of N elements at instant n, Eq. (6.15) is obtained.

$$\boldsymbol{x} = \left[x(n), x(n-1), ..., x(n-N+1)\right]^T . \tag{6.15}$$

The equation for s can be rewritten in terms of *x(n)*, and it is given by Eq. (6.16).

$$\begin{aligned} \boldsymbol{s} = \{ & x(n), \sin[\pi x(n)], \cos[\pi x(n)], ..., \sin[(2P+1)\pi x(n)], \cos[(2P+1)\pi x(n)], \\ & x(n-1), \sin[\pi x(n-1)], \cos[\pi x(n-1)], ..., \sin[(2P+1)\pi x(n-1)], \\ & \cos[(2P+1)\pi x(n-1)], ..., x(n-N+1), \\ & \sin[\pi x(n-N+1)], \cos[\pi x(n-N+1)], ..., \sin[(2P+1)\pi x(n-N+1)], \\ & \cos[(2P+1)\pi x(n-N+1)]\}^T \end{aligned} \tag{6.16}$$

6.2. DESIGN OF ANC BY HYBRID FLANN AND FIR

Perceptions of different structures and algorithm uncover that the structures are either intricated or algorithms utilized are computationally costly. Consequently, there is a potential requirement for basic nonlinear control structure that is temperate to execute and would offer in any event comparable or superior to execution than the current procedures. By this view, the present examination has been done to advance a basic nonlinear controller for dynamic control of nonlinear noise forms.

A solitary layer functional link artificial neural network (FLANN) has been utilized to build up filtered-s LMS (FsLMS) algorithm to accomplish this goal. A quick usage plan of FsLMS algorithm has likewise been proposed. Another filtered-s LMS algorithm and its quick execution plot are produced utilizing the FLANN structure. Examination of the computational unpredictability of FsLMS and FxLMS algorithm is additionally used. Appropriateness of FsLMS algorithm in alleviating a nonlinear commotion process with a nonminimum-stage optional path gauge of the ANC framework is prepared.

By evaluating the approach of FLANN structure dependent on FsLMS algorithm, which is normally utilized in the nonlinear active noise control (NANC) system. It tends to be discovered that the controller coefficients of nonlinear parts are numerous linked and this issue makes unbalance to determine coefficients and restrictions the execution of FsLMS algorithm.

An ANC system is designed with a hybrid combination of functional link artificial neural network (FLANN) and FIR filter (George and Panda, 2012). FF algorithm is used to measure the filter coefficients of FLANN and FIR filters. Normalized mean square error (NMSE) value is computed through FsLMS algorithm. The proposed method has faster convergence and improves the effectiveness of the system. Figure 6.2 shows the hybrid combination of FLANN and FIR filter.

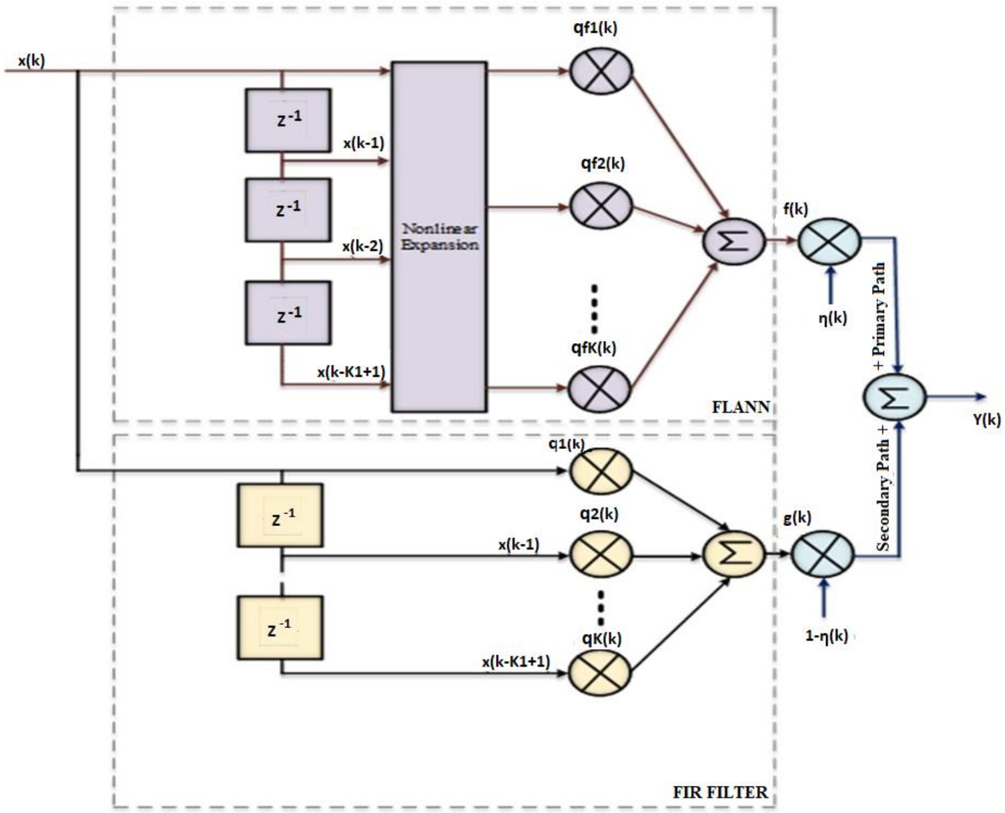


Figure 6.2: Hybrid combination of FIR and FLANN for ANC

An ANC system based on an adaptive combination of FIR filter and FLANN is developed. FF algorithm for updating the weights of the new controller is also derived. The proposed FIR-FLANN nonlinear controller has been shown in Fig. 6.2. The two major elements of the structure are FLANN and an adaptive FIR filter.

The noise signal is the input signal given to FLANN via delay elements. After the computation of delay elements, the noise has given a nonlinear expansion. These outputs are multiplied with the filter coefficients. For this purpose, multipliers are used. Filter coefficients are computed through FF algorithm. NMSE is evaluated by FsLMS algorithm. All the outputs are added together to get the final output of FLANN.

The output obtained from FLANN is given as the input of FIR filter. Here also delay elements are to be computed. FF algorithm updates filter coefficients in the same manner as that of FLANN algorithm. Filter coefficients are multiplied with the delay elements. All outcomes are added up to get the FIR output signal. Filtered FIR output multiplied with the learning parameter to obtain reduced noise signals.

A hybrid combination of FLANN and FIR filters are used in the proposed work. Filter coefficients are evaluated through FF algorithm. NMSE is computed using FsLMS algorithm. The proposed method can improve the convergence as well as the effectiveness of the system. Noise reduction is done primarily by FLANN and then by the FIR filter.

6.2.1 FLANN design

The relatively simpler structure and lower computational complexity of the FLANN filter have led to enhanced interest in FLANN filter based ANC systems over the ones based on multilayer neural networks. The input to FLANN filter is transformed into nonlinearly related elements using a suitable basis function which can be trigonometric, exponential or Chebyshev. These expansions map the linear input into nonlinear ones and also increases the dimensionality of the structure. This leads to the development of a nonlinear ANC with improved performance. Let K_1 be the number of terms obtained after the nonlinear expansion of a set of K tap delayed input samples. If the input pattern is defined as $I(k)=[x(k),x(k-1),\ldots,x(k-K+1)]^T$, the trigonometric expansion of the input vector is given by Eq. (6.17).

$$\begin{aligned} X(n)=\big[&x(k),\sin(\pi x(k)),\cos(\pi x(k)),\ldots,\sin(\gamma\pi x(k)),\cos(\gamma\pi x(k)),\ldots, \\ &x(k-K+1),\sin(\pi x(k-K+1)),\cos(\pi x(k-K+1)),\ldots, \\ &\sin(\gamma\pi x(k-K+1)),\cos(\gamma\pi x(k-K+1))\big]^T \end{aligned} \tag{6.17}$$

Order of the FLANN filter is γ.

A total number of terms in the expanded vector is $K_1 = K(2\beta+1)$.

Filter coefficients of the FLANN filter are given by Eq. (6.18).

$$Q_f(k)=\left[q_{f_1(k)}q_{f_2(k)}\cdots\cdots q_{f_{K_1(k)}}\right]^T \tag{6.18}$$

These elements are updated through FF algorithm. In Eq. (6.18) $Q_f(k)$ is the filter coefficients of FLANN filter. It can be updated by FF algorithm. The updated value is derived by,

$$Q_f(k+1) = Q_f(k) + \mu e(k)\tilde{X}(k) \tag{6.19}$$

In Eq. (6.19) $e(k)$ is the residual noise, μ is the learning parameter and $\tilde{X}(k)$ is the functionally expanded input signal vector filtered through the model of the secondary path. $\tilde{X}(k)$ is found out in Eq. (6.20).

$$\tilde{X}(k) = X(k) * \hat{r}(k) \tag{6.20}$$

In Eq. (6.20), $\hat{r}(k)$ is the impulse response of the secondary path model.

The output of FLANN is given by Eq. (6.21).

$$f(k) = Q_f^T(k)X(k) \tag{6.21}$$

6.2.2. FIR filter design

The output equation of the FIR filter is expressed by,

$$g(k) = Q^T(k)X_a(k) \tag{6.22}$$

In Eq. (6.22), $Q(k) = \left[q_1(k)q_2(k)\cdots\cdots q_{k_2}(k)\right]^T$, is the weight vector of FIR filter at time k and $X_a(k) = \left[x(k)x(k-1)\cdots\cdots x(k-K_2+1)\right]$ represents the tap delayed input signal vector.

The overall output of the adaptive controller is expressed by,

$$y(k) = \eta(k)\, f(k) + \left(1-\mu(k)\right)g(k) \tag{6.23}$$

In Eq. (6.23), $\eta(k)$ is the adaptive parameter between 0 and 1, which governs the combination ratio of the two networks.

Feedback is not provided by FIR filter. This type of configuration can improve the stability of the system and can reduce the noise level.

6.3 PERFORMANCE ANALYSIS BY HYBRID FLANN-FIR FILTERS

From the active noises such as Gaussian noise, Flicker noise, Brownian noise, pink noise etc. the chaotic noise signal and Gaussian noise signal are selected for analysis. Chaotic noise has gained importance these days. No work has been reported as yet where feedback ANC is used for controlling chaotic noise which is broadband in nature. The chaotic noise is a nonlinear deterministic noise and is generated from dynamic systems such as fans, blowers, grinders and airfoils, etc. Furthermore, the secondary path, which is the path from the output of the controller till the error microphone input, shows non-minimum phase response. This imposes the ANC to act as a predictor. This is because the secondary path is placed after the ANC block and hence ANC ultimately has to model the inverse of the secondary path. If the secondary path is the non-minimum phase, whose inverse does not exist, but a causal inverse exists, forces the ANC to be predictable. Therefore, a chaotic noise, which is nonlinearly predictable noise, can be controlled by a nonlinear controller. Conventional ANC systems with a linear controller using filtered-x least mean square (FxLMS) algorithm provides poor performance, and sometimes even fail to control such type of noise. Therefore, for the mitigation of chaotic noise, nonlinear controllers are employed, which provide a better result than that obtained with linear controllers. Researchers have proposed various nonlinear controllers such as radial basis function neural network, artificial neural networks (ANN), functional link artificial neural networks (FLANN) based on trigonometric or piecewise linear functional expansions, functional link neural networks (FLNN) and adaptive Volterra filters, bilinear filter, etc.

Additive white Gaussian noise is a basic noise model used in Information theory to mimic the effect of many random processes that occur in nature. The modifiers denote specific characteristics: Additive because it is added to any noise that might be intrinsic to the information system. Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed.

The proposed ANC system with the FLANN-FIR using FF and filtered-s least mean square (FsLMS) algorithms are more advantageous than the ANC systems using Volterra filtered-x least mean square (VFxLMS) algorithms because of their better performance and less computational complexity.

6.4 PROPOSED METHOD ANALYSIS

The proposed method is analyzed with a Gaussian noise signal and chaotic noise signal. Simulation results are explained below. The obtained results are compared with the results of another recent algorithm. Table 6.1 shows the comparison of the combined FLANN+FIR+FF+FsLMS algorithm with MFsLMS+HPSOFF combined for the Gaussian noise signal shown in Fig. 5.8 and chaotic noise signal is shown in Fig. 5.5.

Table 6.1: Comparison of the combined FLANN+FIR+FF+FsLMS algorithm with MFsLMS+HPSOFF combined for the Gaussian noise signal and chaotic noise signal

S.no	Method	NMSE(dB) Gaussian Noise Signal	NMSE (dB) Chaotic Noise Signal
1	MFsLMS+ HPSOFF	0.187	0.265
2	FLANN+FIR+FF+FsLMS	-1.1	-1.4

6.4.1 GAUSSIAN NOISE SIGNAL

Gaussian noise is represented by Fig. 6.3, in which time is gone up against x-axis, and frequency esteem is given on the y-axis. In this figure, the Gaussian noise is scattered around the waveform. The amplitude value of the given Gaussian noise ranges between 0.7 and 4.1.

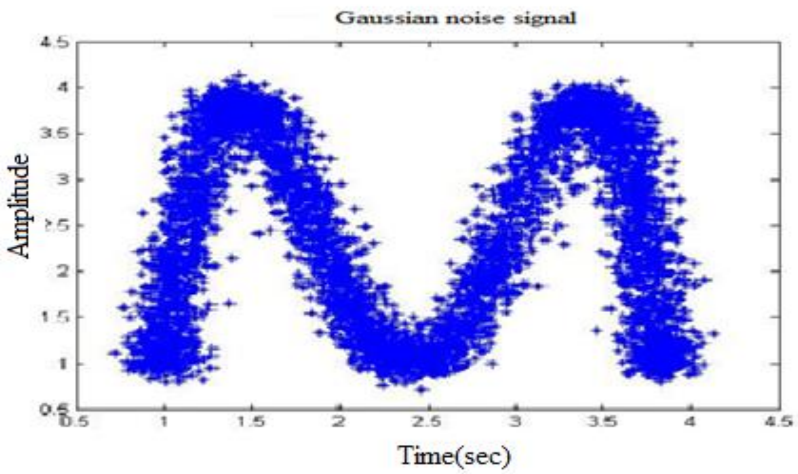


Figure 6.3: Input gaussian noise signal

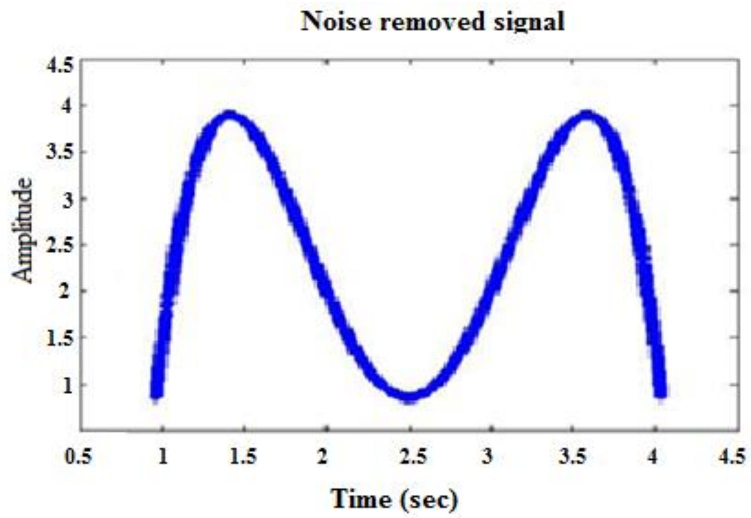


Figure 6.4: Denoised signal by the proposed ANC system with FF algorithm

Better noise reduction can be achieved with a Gaussian noise using the proposed methodology. Fig. 6.4 is an amplitude versus time diagram of the noise cancelled signal. The total decrease of noise levels from the actual signals with diminished amplitude levels is acquired. The amplitude value is reduced in the range of 0.8 and 3.9.

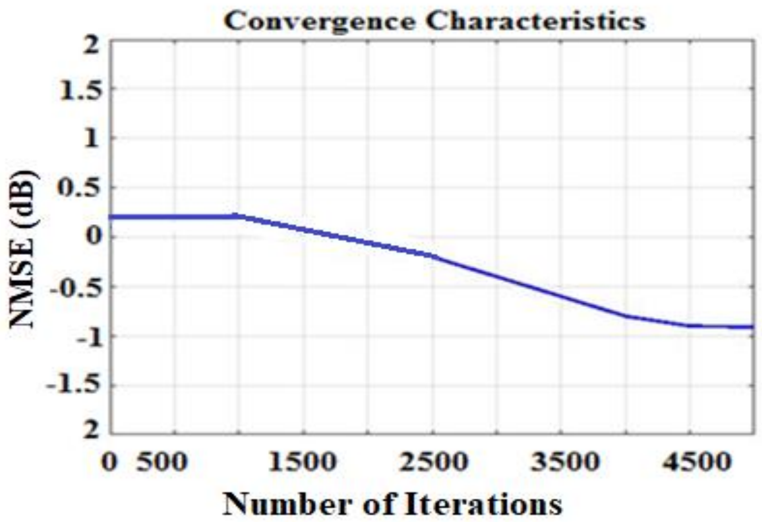


Figure 6.5: Convergence characteristics of proposed ANC system with FF algorithm

Figure 6.5 shows the convergence curve. More than 4500 iterations have been taken for an accurate result. Less value of NMSE means a good convergence. Therefore, from the graph, it is evident that the proposed methodology can improve the convergence characteristics. There is a continuous reduction in the value of NMSE. Convergence became maximum at the last iteration. The curve starts from a high positive value of NMSE in the first iteration. Then up to 1000 iterations, there are no variations in the value of NMSE. After that, the parameter value decreasing to a negative value. The NMSE value is reduced from 0.2 dB to the least value obtained is -0.9 dB.

6.4.2 CHAOTIC NOISE SIGNAL

The Chaotic noise signal is shown in Fig. 6.6 that is scattered around the waveform. The amplitude value of the given Chaotic noise ranges between-0.3 to 3.

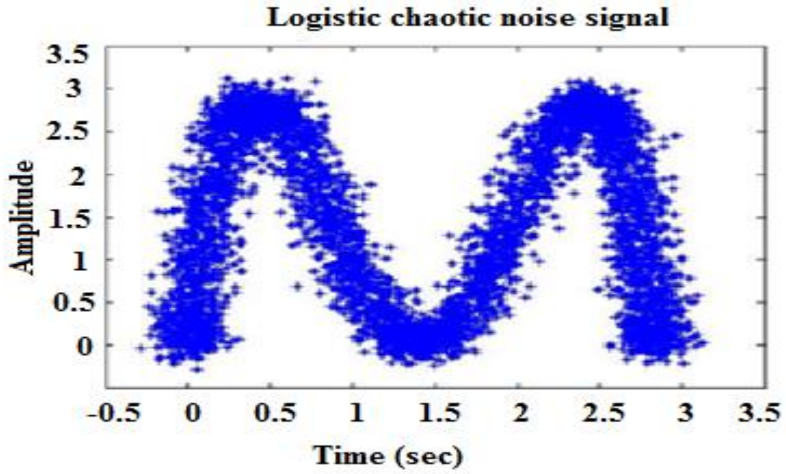


Figure 6.6: Input chaotic noise signal

In the Fig. 6.6 input chaotic waveform is plotted between amplitude on y-axis versus time on x-axis. From this figure, the amplitude value varies between a minimum value of 0.3 and to a maximum value of 3 randomly. There is a high level of noise in the given signal. The proposed method can be applied in this waveform to reduce the noise level.

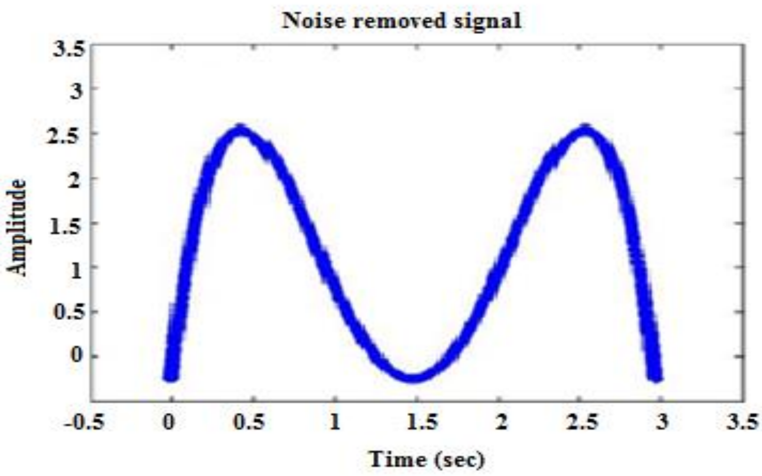


Figure 6.7: Denoised signal by the proposed ANC system with FF algorithm

Figure 6.7 is the denoised signal after the implementation of the proposed methodology. By analyzing the figure, the amplitude varies from a minimum value of -0.3 and to a maximum value of 2.6. Thus, the noise level is perfectly reduced. Almost all the noises are removed.

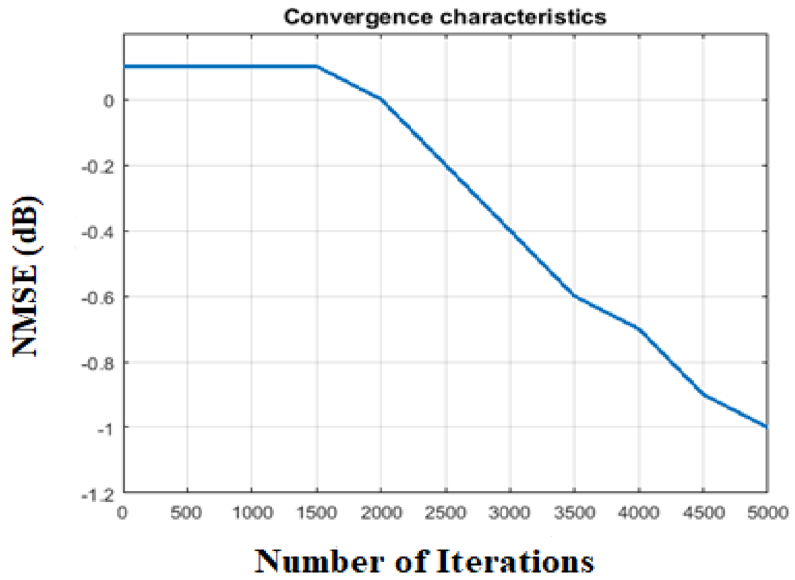


Figure 6.8: Convergence characteristics of proposed ANC system with FF algorithm

Figure 6.8 is the convergence curve of the proposed ANC system. Like that of Gaussian noise, the convergence of the ANC system is improved with the chaotic noise signal. NMSE value starts from a positive value of 0.5 dB and reduces to -1 dB after 1500 iterations. Then the parameter decreases steeply up to a negative value. The least value obtained after 5000 iterations is -1db. As the error value decreases, the convergence improves. Thus, high efficiency can be attained with the proposed method.

6.5 COMPARISON

6.5.1 BAT ALGORITHM

A comparative study is carried out between the proposed one and BAT algorithm to evaluate the performance of the system compared to other existing algorithms. Analysis of the system is done similarly. Chaotic and Gaussian noise is also considered here for performance evaluation. In this study, the FF algorithm is replaced with BAT algorithm. FF algorithm is used for updating the filter coefficients.

Gaussian noise signal

The same input signal given in Fig. 6.3 is used. Denoised signal with the BAT algorithm is given in Fig. 6.9. The denoised output waveform is entirely different. The noise amplitude ranges between 0.8 and 4.0. Therefore, with Gaussian noise, the noise level is not properly mitigated. The output waveform contains a high level of noise hence compared with the proposed methodology. Thus, FF algorithm is the better optimization technique than BAT algorithm for Gaussian noise.

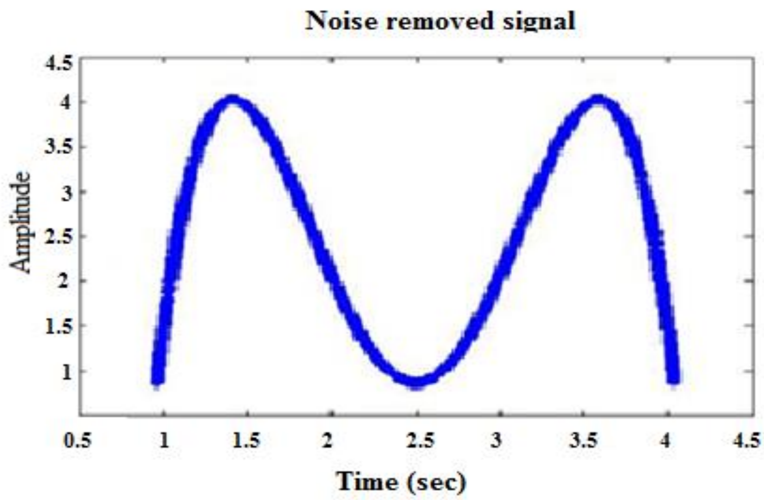


Figure 6.9: Denoised signal by the proposed ANC system with BAT algorithm

Figure 6.10 shows the convergence characteristics with BAT algorithm. NMSE value varies from 0 value to -1.2 dB. In effect after 4500 iterations, the convergence of the system gets improved. Therefore, BAT algorithm can increase the convergence of the system, but the noise reduction is poor. It is concluded that the FF algorithm can simultaneously improve noise reduction and convergence of the system.

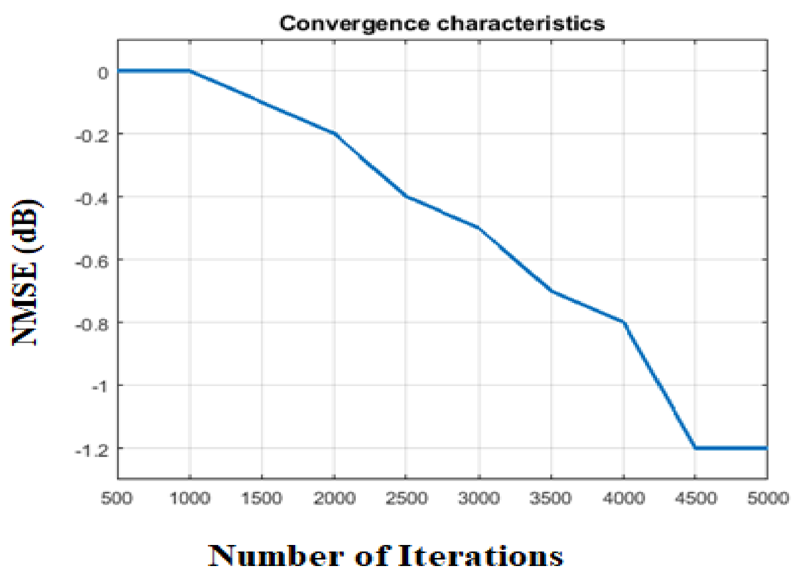


Figure 6.10: Convergence characteristics of proposed ANC system with BAT algorithm

The parameters used for the simulation are given in Table 6.2 for the proposed algorithm and BAT algorithm. For the proposed algorithm light intensity, light absorption coefficient, number of fireflies, lower and upper bound, number of iterations etc. are given. For the BAT algorithm population size, the number of generations, loudness, etc. are provided. Number of iterations is fixed at 5000 for both algorithms

Table 6.2: Simulation parameters of BAT and FF algorithm

BAT algorithm		**Firefly algorithm**	
Population size	10	Light intensity	0.8
Number of generations	5000	Light absorption coefficient	1
Loudness	0.1	Number of fireflies	10
Pulse rate	0.022	Lower bound	0
Minimum frequency	0	Upper bound	2
Maximum frequency	2	Number of iterations	5000
Lower bound	-2	Length of the secondary path	L
Upper bound	2	N_t	10
		β	3
		Number of terms N_2= 6, N_3=7	
		Learning parameter $\mu = 4 \times 10^{-2}$	

Table 6.3: Comparison results for Gaussian noise

Parameters	**FF Algorithm**	**BAT Algorithm**
Input signal	Gaussian noise	Gaussian noise
Output signal	De noised signal	De noised signal
Amplitude	0.8 to 3.9	0.8 to 4.0
NMSE (dB)	0.2 to -0.9	0 to -1.2

The comparison results for BAT algorithm with the proposed methodology is tabulated as in Table 6.3 The same Gaussian noise given input for both algorithm analysis. De-noised signals are obtained as output from both algorithms with different amplitude and NMSE values. For BAT algorithm the amplitude varies from 0.8-4.0, and the NMSE value is reduced from 0 dB to negative value of -1.2 dB. But for the proposed algorithm, denoised signals have an amplitude range of 0.8 to 3.9. NMSE value reduced from 0.2 dB to -0.9 dB. Thus, for both cases, the output is obtained as a denoised signal. But the noise cancellation process is better in the case of the proposed algorithm, and that is poor for the BAT algorithm. From the convergence curve, the NMSE values are obtained. Finally, from the comparison results of both the methods proposed methodology can be applied to an ANC system for good noise reduction with satisfied convergence rate. BAT algorithm has good convergence, but the noise reduction performance is poor.

Chaotic noise signal

The same Chaotic noise signal shown in Fig. 6.6 is used for the here for the comparison. The denoised signal obtained after the simulation is presented in Fig. 6.11. The time varies from 0 to 3.0 seconds, and amplitude ranges from -0.3 to 2.8. Figure 6.12 shows the convergence characteristics of proposed ANC using BAT algorithm.

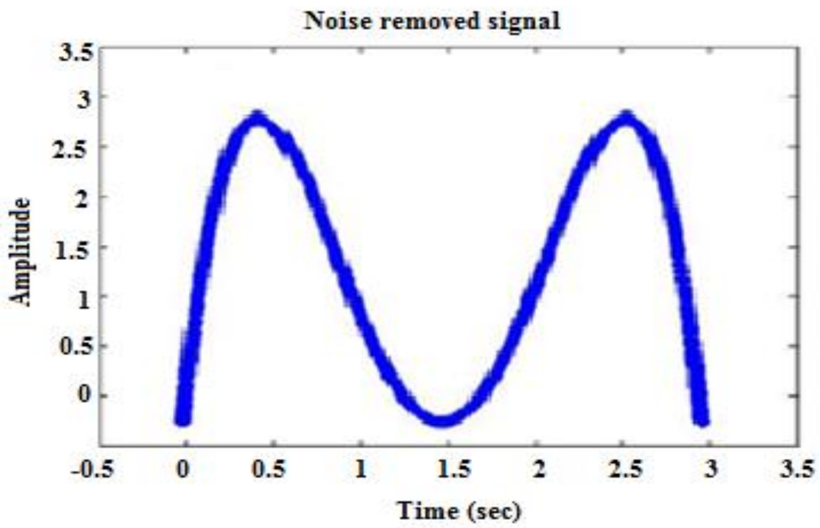


Figure 6.11: Denoised signal by the proposed ANC system with BAT algorithm

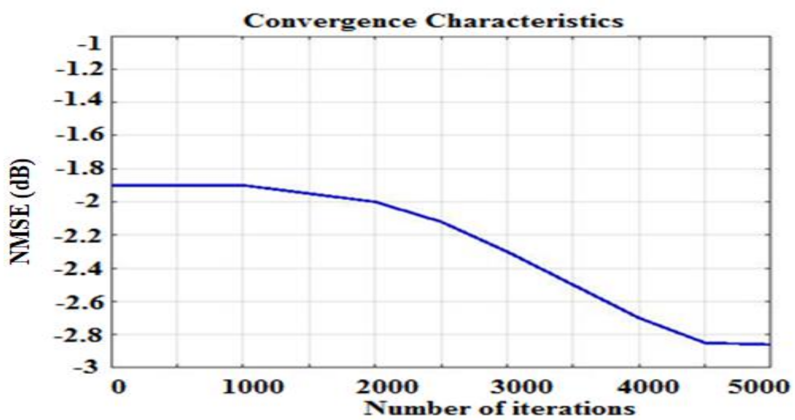


Figure 6.12: Convergence characteristics of proposed ANC system with BAT algorithm

Table 6.4: Comparison results for chaotic noise

Parameters	FF Algorithm	BAT Algorithm
Input signal	Chaotic noise	Chaotic noise
Output signal	Denoised signal	Denoised signal
Amplitude	-0.3 to 2.6	-0.3 to 2.8
NMSE	0.5 to -1	-1.9 to -2.85

The comparison of the results for the chaotic input signal is given in Table 6.4. The chaotic signal with the same amplitude and frequency is given as input for both the algorithm simulations. The denoised signal is obtained. In the case of BAT algorithm, the denoised signal amplitude is from -0.3 to 2.8. The NMSE value reduced from -1.9 dB to -2.85 dB. Thus, convergence and noise reduction are obtained. For FF algorithm the denoised signal waveform has an amplitude of -0.3 to 2.6. The NMSE value is from 0.5 dB to -1 dB. From the results, it can conclude that noise reduction and convergence improvement are satisfied.

6.6. IFLANN-FsuLMS

The comparison of the computational complexity of the proposed methodology and existing IFLANN-FsuLMS algorithm (IIR functional link artificial Neural Network- Filtered su least mean square algorithm) is given in Table 6.5. In Table 6.5, the number of multiplication and addition operations are compared. For the IFLANN-FsuLMS the weight updating is done with FsuLMS algorithm (George and Panda, 2012). In the proposed methodology, the weight updating is done with FF algorithm. The number of multiplication and additions of the IFLANN-FsuLMS and the proposed algorithm have been presented in Table 6.5. The number of multiplication and additions used by proposed method is lower compared to the existing IFLANN-FsuLMS algorithm, where L is assured as the length of the secondary path. The computational complexity has been reduced when the proposed method is used.

Table 6.5: Comparison results for Gaussian noise

Scheme	**IFLANN-FsuLMS**		**Proposed Method**	
Operation	Multiplications	Additions	Multiplications	Additions
Controller output	N_1+N_2+N_3+2	N_1+N_2+N_3	N_2+N_3+2	N_2+N_3
Filtered signal	[N_1+N_2+N_3+3]L	[N_1+N_2+N_3+3] (L-1)	[N_2+N_3+2]L	[N_2+N_3+2](L-1)
Weight update	N_1+N_2+N_3+7	N_1+N_2+N_3+5	N_2+N_3+7	N_2+N_3+5
Total	(N_1+N_2+N_3)+3L+9	(N_1+N_2+N_3)(L+1) + 3L+2	(N_2+N_3)+3L	(N_2+N_3)(L+1)+3L

6.7 SUMMARY

This chapter presents the design procedure of the ANC system using the hybrid functional link artificial neural network (FLANN) and finite impulse response (FIR) filter for the effective reduction of noise. The trigonometric functional expansion is used in the ANC scheme of the hybridized FLANN, and FIR filter is described in this chapter. The performance analysis of hybrid FLANN and FIR filter is carried out in terms of normalized mean square error (NMSE) by the comparison of FF algorithm and BAT algorithm. The gaussian and chaotic noise signals are used for the simulation done in this chapter. The computational complexity of the proposed methodology and existing IIR functional link artificial Neural Network- Filtered su least mean square algorithm (IFLANN-FsuLMS) algorithm has been compared.

CHAPTER 7

CONCLUSIONS AND FUTURE SCOPE

7.1 CONCLUSION

The problem of controlling the noise level in the environment has been the focus of a tremendous amount of research over the years, and noise control has gained considerable importance in recent years. In this research, a modified filtered-s least mean square (MFsLMS) algorithm, which is a modified version of the FsLMS algorithm is presented in chapter 4. In the next chapter, the stability of the system is taken as an important factor. So that a hybrid optimization is introduced to improve stability. Superior optimization techniques are chosen for the purpose. Chapter 6 of the thesis proposes a hybrid filter combination for the convergence improvement and effectiveness of the system. These methods of noise reduction are analyzed with some noise signals. These results are presented in chapter 5 and 6.

Passive noise control techniques work well at high frequency, but these are ineffective or impractical at low frequency. The ANC is an alternative, wherein an anti-noise is generated to eliminate the undesired noise by using the principle of destructive interference. The controller of the ANC systems can be either non-adaptive or adaptive depending on the properties of the noise field. The amplitude and frequency of the unwanted noise do not remain constant in practical situations. The noise may distort with the change in the environmental conditions like pressure, temperature and component ageing, etc. Therefore, for the effectiveness of the ANC system to these changed conditions, the controller needs to be adaptive. The ANC system is further classified as feedforward and feedback depending upon the availability of the coherent reference input. In feedforward ANC systems, the reference input is provided by a reference microphone. But in feedback ANC, there is no reference microphone, and the reference input is estimated from the error microphone signal. The drawback of the feedforward ANC system is that because of the presence of the reference microphone, the secondary source (loudspeaker) output may get feedback to the reference microphone signal, and it may degrade the performance of the ANC system. But since there is no reference microphone in feedback ANC, there is no such feedback of the secondary source output. Another drawback of the feedforward ANC system is that, if there are multiple noise sources, then multiple reference microphones are required to provide multiple reference inputs, and multiple adaptive filters are required for the adaptation purpose of each input. Therefore, in these cases, the system becomes complicated and expensive. But in a feedback ANC system, there is no reference microphone, and hence only one adaptive filter is required. Therefore, it is computationally, efficient and economical for multiple references.

Various algorithms for ANC have been studied and compared. Five models for the cancellation of Noise have been discussed, LMS Algorithm, Filtered-x LMS algorithm, FsLMS algorithm, FLANN Filter, Particle Swarm Optimization Algorithm. The first two are mainly in the presence of linear noise varying environment; the latter has a successful implementation in the presence of linear as well as non-linear noise.

In this work, a modified version of the existing FsLMS algorithm is adopted. The results show that modified Filtered-s LMS provides better attenuation of noise as compared to the counterpart LMS Algorithm which is simple and easy to implement, comparatively. FLANN Filter gives a better output compared to the other methods in the presence of non-linearity, though the error increases as the nonlinearity in the environment increases.

MFsLMS algorithm is one of the novel algorithms used for the ANC. More complex alternatives require more computational power and for the cases where the noise can be modelled with measurable parameters obtained from the system, increased the number of acoustic or non-acoustic sensors. Especially, alternatives which are more robust to non-linearities due to time-variant characteristics of the acoustic paths and the characteristics of noise itself can be employed for the control of environmental noise. Integration of more robust control algorithms to use of the ANC system against environmental noise is crucial for sustainable performance. Ease of application makes ANC systems a powerful potential solution.

Scalable and lightweight characteristics of ANC systems promises portable implementations, as well as arrays of systems, may be cascaded in order to extend the effective range. The performance of the proposed system is investigated through case studies. The study shows that the proposed system can decrease low-mid and mid-frequency components of chaotic and Gaussian noise.

When the advantages of the ANC systems over passive noise controllers are set aside, only a few disadvantages appear. The main disadvantage of ANC systems arises from its electronic-based architecture. The ageing of the electronic and electro-acoustic components may result in a decreased performance. Hence, ANC systems should be maintained regularly and worn of components should be replaced. However, its small scale, high performance and modular application possibilities make ANC superior to passive noise regulators.

With the advances in technology, digital signal processing approaches and hardware, potentials of the ANC will realize, resulting in better control performance while decreasing in scale and cost. The most critical issue to be considered for the implementation of such a system should be stability. An unstable ANC system can cause an increase in noise as the reproduced control signal becomes unstable. A control signal produced by an unstable control system becomes noise itself and adds up to the present noise resulting in the overall increase. Hence, noise characteristics, available system components, control strategy to be applied, and the working frequency of the system should be carefully determined in order to ensure stable operation. Stability improvement techniques are also proposed in this work.

In this thesis, new signal processing methods are considered in two approaches to improve the performance of active noise control systems. In the first approach, the concept of the FsLMS algorithms is considered. This approach is called modified FsLMS (MFsLMS), and it outperforms the conventional FsLMS based ANC systems under the situation of large measurement of noise. For further improving the performance of convergence and stability of system, hybrid PSO-FF algorithm is used with MFsLMS.

The second approach proposed a hybrid filter called FLANN-FIR filter. In which the filter coefficients are estimated through the FF optimization algorithm. It is used for the weight updating process. NMSE value is computed by using FsLMS algorithm. This approach proved to provide better convergence and effectiveness of the system.

Finally, the performance analysis of the two methods is given with two types of noise signals. A very good noise reduction is obtained after the implementation of the proposed approaches.

7.2 FUTURE SCOPE

In this thesis, an ANC system is proposed, which can be used for noise reduction in open spaces where high noise is present, and the use of sound barriers is not possible or adequate. The proposed active noise controllers can be used on sites where the noise exposure limits are exceeded. Unlike conventional passive noise barriers, working with the principle of controlling the noise on the source, the proposed system brings the idea of controlling the noise at the receiver point or in the neighbourhood. Hence, the required space is also decreased compared with bulky passive sound barriers. This study has pioneering characteristic by means of application of active noise control at outdoor spaces and areas as well as in urban scale.

Moreover, scalable size and the effect of the system make it applicable to special cases where architectural solutions are important.

In future, active noise barriers can be integrated with smart city systems, enabling the employment of noise specific algorithms for changing characteristics of the noise source within a day. Even system may be taken offline for the specific hours of a day when the environmental noise is below limiting values, in order to save energy.

Since the selection of the right noise reduction procedure plays a major role, it is important to experiment and compare the methods. As future research, the work could be carried further on the comparison of the noise reduction techniques. The features of the denoised signal could be applied to the different types of optimization technique like Swarm Intelligence (SI): Ant Colony Optimization (ACO), Cat Swarm Optimization (CSO), further, the future scope of this work could be focused to produce a better solution by improving the effectiveness and reducing the existing limitations.

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