

NONLINEAR ACOUSTIC ECHO CANCELLATION  
USING ADAPTIVE ALGORITHMS  
UNDER NOISY ENVIRONMENT

*A Dissertation Submitted in Partial Fulfillment of the Requirement for the Award of the  
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Submitted By

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## DECLARATION

I, **Jashu Sharma**, hereby declare that the work thesis entitled “**Nonlinear acoustic echo cancellation using adaptive algorithms under noisy environment**” is a record of my own work carried out towards the partial fulfillment for the award of degree of Master of Engineering submitted in Electronics and Communication Engineering Department, Thapar University, Patiala, under the guidance of **Dr. Amit Kumar Kohli**, Associate Professor, ECED, Thapar University, Patiala, during 2016-2017.

The matter presented in this has not been submitted either in part or full to any other university or institute for the award of any other degree.

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## ABSTRACT

This research work presents a nonlinear-acoustic-echo-cancellation (NAEC) technique to tackle sigmoid-type nonlinearities under the noisy environment. The performance of NAEC technique is investigated for both cases, in the presence of environmental noise and in the absence of environmental noise. The nonlinear echo in acoustic systems is inevitable due to the inherent nonlinear characteristics of amplifiers and/or loudspeakers, which deteriorates the quality of speech as well as audio signal reception.

Here, the sigmoid-type nonlinearity is modelled by using two control parameters, which determine the shape and clipping value of the saturation curve. These control parameters are adjusted by using variable-step-size (VSS) least-mean-square (LMS) adaptive algorithms to enhance the convergence rate and tracking capability, under the noisy environment. Two VSS-LMS algorithms are utilized, which are RVSS-LMS (as proposed by Kwong and Johnston; IEEE Trans. Sig. Proc., 1992) and TMVSS-LMS (as proposed by Aboulnasr and Mayyas; IEEE Trans. Sig. Proc., 1997) algorithms. The impulse response of acoustic echo path in a room is modelled as a tap-delay-line finite-impulse-response (FIR) filter, whose tap-coefficients are estimated by using the recursive-least-square (RLS) algorithm at the different values of signal-to-noise-ratio (SNR), when the correlated as well as uncorrelated input signals are processed. The uncorrelated input signal samples are considered to be Gaussian random variable with zero-mean and unity variance. The correlated input signal samples (with zero-mean and unity variance) are assumed to follow a first-order autoregressive process i.e., AR(1) process in one case and a second-order autoregressive process i.e., AR(2) process in other case. The performance of various VSS-LMS and RLS algorithm based NAECs is also compared with VSS-LMS and NLMS algorithm based NAECs, under similar conditions.

In the research work presented in this thesis, only single talk case is considered in all input cases. Simulation results are presented to demonstrate the efficiency and efficacy of the NAEC technique using the adaptive algorithms in terms of the fast convergence rate and the high value of echo-return-loss-enhancement (ERLE) factor. The presented results connote that the NAEC technique based on TMVSS-LMS and RLS algorithm provides best results, in comparison to the RVSS-LMS and RLS algorithm based NAEC strategy. However, the fixed-step-size (FSS) LMS and NLMS algorithms fail to outperform the VSS-LMS and RLS algorithm based

**NAECs under similar conditions. It is evident from results that TMVSS-LMS and RLS algorithm based NAEC performs exceptionally well in case of the AR(2) correlated input, as compared to the AR(1) correlated and Gaussian uncorrelated inputs.**

**Keywords: Acoustic-echo-cancellation (AEC), Sigmoid function, VSS-LMS, NLMS, RLS, ERLE**

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AEC	Acoustic Echo Canceller / Cancelling
APA	Affine Projection Algorithm
AR	Auto Regressive
DFT	Discrete Fourier Transform
ECG	Electrocardiogram
EEG	Electroencephalogram
ERLE	Echo Return Loss Enhancement
FIR	Finite Impulse Response
FLAF	Functional Link Adaptive Filter
FLN	Functional Link Network
FSS-LMS	Fixed Step-size Least Mean Square
GA	Genetic Algorithm
KLMS	Kernel Least Mean Square
LA	Lattice Algorithm
LMP	Least Mean $p^{th}$ power
LMS	Least Mean Square
LS	Least Squares
MMSE	Minimum Mean Square Error
MSE	Mean Squared Error
NAEC	Nonlinear Acoustic Echo Canceller / Cancelling
NARMAX	Nonlinear Autoregressive Moving Average with Exogenous Inputs
NLMS	Normalized Least Mean Square
PA	Power Amplifier
PSO	Particle Swarm Optimization
RLS	Recursive Least Square
RVSS-LMS	Robust Variable Step-size Least Mean Square
SD	Steepest Descent
SNR	Signal to Noise Ratio
TMVSS-LMS	Tyseer's Modified Variable Step-size Least Mean Square
VF	Volterra Filter
VSS-LMS	Variable Step-size Least Mean Square

# CHAPTER 1

## INTRODUCTION

Transforming from analog to digital signaling, from narrowband to wideband audio processing, from wireline to wireless devices, and from circuit-switched to packet-switched systems, some extraordinary advancements have taken place in field of telecommunication engineering ever since A.G. Bell innovated the telephone in 1876. But, conversation as well as collaboration utilizing present day voice communication engineering is still complex. The hindrance of holding redundant equipment like a close-talk microphone and deficiency of sensibility of distinct speaking environments results in reduced interaction as well as productivity, and sooner or latter causing client dissatisfaction. This is not considered as grandeur, but there is actually a logical need to design a life-like voice communication system that provides the communicating parties a feeling of being in the similar acoustic scenario, which is usually termed as “immersive experience” in the domain of multimedia communication. To attain such target, one of the hazards, which ought to be investigated, is acoustic echo cancellation. In hands-free telephone equipments, internet phones and teleconferencing equipments, the coupling between a loudspeaker and microphone on one side of system causes echoes to arise, which deteriorates audio quality for the listener on other side. For this reason, this is usually necessary to employ an acoustic-echo-canceller (AEC). An AEC greatly boosts audio quality, which permits conferences to progress more smoothly, and prevents listener fatigue. Echo cancellers have been explored in preceding decades. A large number of AEC designs search to eliminate the echo by reconstructing and subtracting the estimate of this echo signal from microphone-received signaling waveform. It is carried out by modelling the acoustic echo path by utilizing the adaptive filter. The acoustic echo path can also be tracked automatically, and which is viewed as the system identification problem. Firstly, this is executed with the aid of modelling the acoustic echo path using adaptive Volterra filters [1] – [9]. However, the adaptive filter is required to perform well in the presence of interference and ambient noise, while tackling the system identification. Therefore, two major design problems for AECs are

- 1) Adaptive filtering procedures design
- 2) Control logic design for filter adaptation

The first design problem focuses on filter adaptation. A number of adaptive filtering procedures are suggested to eliminate/suppress echoes, while dealing with full-duplex communication systems. The well-adopted techniques include an adaptive Volterra filtering

[2], [3], and least-mean-square (LMS) procedure [24], [25], [30]. Several schemes based on the affine-projection-algorithm (APA) or recursive-least-square (RLS) procedure [29], [30], [32] have been reported to cope with an ill-conditioned input autocorrelation matrix that deteriorates characteristics of LMS procedure. Moreover, a current trend in price-competitive audio consumer products has demanded low-cost as well as small-sized analog devices (such as loudspeakers), which often possess nonlinear features. Research outcomes have demonstrated that linear AECs collapse/diverge, when nonlinearity gets involved in acoustic echo path.

In [1], it has been illustrated that performance of the linear AEC is limited by nonlinear constituents in echo path. A few techniques have been reported in archives to suppress nonlinear echo. Moreover, there are disadvantages of existing schemes. Firstly, instability of nonlinear systems is a major concern. Secondly, low convergence rate and large computation burden preclude these schemes from being vastly utilized in real-time applications. Thus, the presented research work on efficient nonlinear-AEC (NAEC) designing/development is well prompted. The simplest among all such adaptive algorithms is the LMS procedure, but it exhibits low convergence speed. In order to enhance convergence rate, (normalized-least-mean-square) NLMS and RLS procedures are utilized. Among these three algorithms, RLS has highest convergence rate and low misadjustment level. Therefore, for highly significant applications, RLS procedure is utilized. In order to make RLS algorithm more efficient, combination of lattice and RLS algorithm is suggested by Sayed and Mathews [1]. It is based upon truncated 2<sup>nd</sup>-order Volterra system. In this case, two lattice-algorithm (LA) based on RLS algorithms are utilized, in which first is the direct extension of RLS linear algorithm and other is QR decomposition of prediction error based extension. These are utilized in nonlinear filtering scenarios, and these perform well in comparison to their linear counterparts. In [2], Panicker and Mathews introduce a parallel as well as cascade approximation of truncated Volterra systems for NAEC, in which bound on the error is attained by utilizing reduced number of branches in such realization and also by cost reduction. AECs in speakerphones and video conferencing equipments are dependent on presumption of a linear echo path. The nonlinear degradations are a superposition of various effects, which could be modelled either as memoryless nonlinearities or as nonlinear systems with memory. Appropriate adaptation methods for both cases of nonlinearities are detailed. An echo cancellation structure for nonlinear systems with memory based on adaptive second-order polynomial filter is reported by Stenger *et al.* in [3]. In order to boost performance of NAECs based on Volterra filtering criterion, a new cascade structure is presented by Guerin *et al.* in [4], which utilizes two modules; one is utilized to model loudspeaker and other is utilized to identify impulse

response of acoustic path. For appropriate working of NAECs based on adaptive Volterra filtering criterion in frequency-domain, Kuech and Kellermann in [5] suggested a partitioned block frequency-domain adaptive Volterra filter.

In [6] – [8], the combination of adaptive Volterra filters and improved adaptive algorithms based on general FIR filter are explored for nonlinear echo cancellation. In [6], the improved tracking capability of a numeric variable forgetting factor RLS procedure is discussed by Kohli and Rai for 1<sup>st</sup>-order and 2<sup>nd</sup>-order Volterra systems under nonstationary environment, which outperforms traditional RLS algorithm; this can also be used for nonlinear echo cancellation, as the acoustic systems are mainly nonstationary and nonlinear in nature. In order to design/develop nonlinear acoustic echo cancellation systems, which can perform better in impulsive noise environment, a new scheme, which utilizes an adaptive polynomial filter utilizing generalized variable step-size LMP procedure is discussed in [7] by Rai and Kohli. This technique is more robust in comparison to other schemes under impulsive noise environment. To boost the efficiency of such Volterra technique based filtering approaches utilized in nonlinear acoustic echo cancellation, a new technique which utilizes two modules in cascade is used in [8] by Rai and Kohli. In this, first is the polynomial Volterra filter, which is utilized to model nonlinear distortion present in acoustic systems due to amplifiers/loudspeakers; and second is simple FIR filter. In order to take the account of room acoustic effects on the performance of NAEC, a strategy, which utilizes combination of nonlinear filter of x-second-order and adaptive Volterra filter, is discussed by Fuster *et al.* in [9]. In this, virtual path concept is utilized. The nonlinearity of loudspeaker in this scheme is represented by a polynomial filter, and linear filter corresponds to electro-acoustic path. After that, problem arises due to the fact that complexity of nonlinear filter increases exponentially with increase in filter's order. In order to get rid of this problem, recursive structures comes into play. The identification of higher-order systems is performed by the usage of 2<sup>nd</sup>-order recursive structures.

A dazzling way to eliminate nonlinear echo constituents from the output of hands-free speakerphones is to use NAECs. First NAEC utilized for this purpose was developed by Nollet and Jones in [10], which is based on Wiener Hammerstein paradigm. This consists of a combination of linear, memoryless nonlinear as well as linear elements. It performs better in comparison to simple nonlinear adaptive filtering schemes. In order to make this scheme more robust and its applications to higher-order adaptive filters are discussed in [11] by Breining *et al.*, and also their adaptation using memoryless nonlinear system is studied by Stenger and Rabenstein in [12]. Due to rising demand of nanotechnology, the handsets get

miniaturized. Due to which, nonlinearity affects more severely in acoustic systems. In order to remove nonlinear echo constituents from these nanohandsets, a bilinear filter i.e., NARMAX filter was reported by Costa *et al.* in [13], which performs better in comparison to linear and nonlinear adaptive filtering techniques. Due to success of this technique, several other schemes for echo cancellation were developed i.e., NAEC using adaptive orthogonalized power filtering configuration in [14] by Kuech *et al.*, which utilizes the orthogonalized type of power filter. It is the cascade of memoryless polynomial as well as linear filter, in which statistics of input signal are not known in advance; and an NAEC using DABNET + FIR structure is discussed by Sentoni and Altenberg in [15]. It is cascade of nonlinear discrete dynamic paradigm and FIR filter. In order to address both problems altogether i.e., acoustic echo and double talk, a new method was presented by Ahgren in [16]. But, latest style in rate-competitive speech patron products have demanded low-fee as well as small-sized analog equipments (including loudspeakers), which typically possess nonlinear features.

Research outcomes have evidenced that linear AECs fail, while nonlinearities get involved in acoustic echo direction. A few methods are presented in archives to eliminate nonlinear echo components from the desired output of the acoustic systems [10] – [16]. But, there are some inevitable hazards in present techniques. First, the stability of nonlinear equipments is hard to be guaranteed. Second, low convergence speed as well as excessive computational complexity preclude their usage and applications in commercial devices. To address such problems, a simple yet efficient NAEC scheme, which utilizes an adaptable nonlinear transformation function in combination with adaptive filtering configuration is presented in [17], [18]. This nonlinear transformation function is utilized to express the effects that are caused because of nonlinearities of amplifiers/loudspeakers, which means this is used to model the saturation curve of loudspeaker and/or amplifier present in the acoustic systems. The benefit of using this nonlinear transformation function is that it can adapt its parameters for both hard as well as soft clipping nonlinearities, and it provides superior quality in comparison to Volterra series based filtering configurations. It exhibits less complexity and computational burden. The objective of this research work is to develop a nonlinear acoustic echo cancelling technique, which utilizes adaptive algorithms in order to suppress nonlinear acoustic echo constituents from the output of acoustic systems, while keeping the computational complexity low.

## 1.1 OVERVIEW OF ACOUSTIC ECHO CANCELLATION

A linear adaptive filtering configuration, filters the data via controlling its adjustable parameters through an adaptive way. The primary factor that generates the idea for developing nonlinear filters inspite of existent a linear filter [19], which fits and works satisfactorily without any difficulty, is the saturation-type nonlinearity that is found in nearly all types of electronic and electrical systems. A number of AEC designs try to suppress the nonlinear echo constituents through reconstructing as well as subtracting the estimate of echo from the waveform received at microphone. Firstly, this is executed with the aid of modelling the acoustic echo path by utilizing adaptive Volterra filters [1] – [9]. In [10], authors indicate that wholistic performance of the linear AEC is dependent on the nonlinear constituents encountered in echo path. Also, a statistical research on LMS procedure proves that even non-significant saturation could deteriorate the output of a linear active noise control system. On the other hand, large reverberation time results in a long room impulse response. More often, an finite-impulse-response (FIR) filter that is utilized to model room impulse response, may spread over hundred to thousand taps [12]. This long room impulse response results in slow filter convergence as well as large computational burden. The emerging nonlinearity in combination with long room impulse response makes the AEC issue more perplexing. Alternatively, large reverberation time results in an extended room impulse response.

The primary form of nonlinearity found in audio and speech systems is the saturation-type of nonlinearity [17]. This nonlinearity of amplifiers and/or loudspeakers conceives nonlinear echo in acoustic systems, which critically deteriorates wholistic performance of communication equipments. To remove these nonlinear components from the acoustic systems, nonlinear Volterra filters, which are adaptive in nature, are utilized by Mathews [20]. This adaptive Volterra filter utilizes truncated Volterra series, which is also called adaptive polynomial filtering configuration [20]. To increase the efficiency of such Volterra filters and to make them robust, many nonlinear acoustic echo cancellation systems had been designed in past years, which are cascade combination of more than one 2<sup>nd</sup>-order Volterra filtering configuration, and these work efficiently in both time as well as frequency-domain [1] – [9]. The sub-band configuration of adaptive Volterra filter is also detailed in [21] by Zhou *et al.*, to enhance efficiency of Volterra filtering schemes. We know that complexity of NAECs increases with the usage of higher-order Volterra filters. In order to alleviate computational burden, many NAECs have been designed, in which nonlinear transformation function is utilized to model nonlinearities present in speech systems in conjunction with adaptive filters to eliminate nonlinear echo constituents. Such nonlinear transformation

functions are easy to handle, and exhibit less computational burden in comparison to truncated Volterra series based filtering configuration. An amazing way to compensate nonlinearity of loudspeaker in acoustic echo cancellation was presented by Dai and Zhu, this technique utilizes raised-cosine characteristic as nonlinear transformation function to model nonlinearity of loudspeaker in conjunction with simple adaptive filter [17]. To remove echo using adaptive filters, Fu and Zhu presented a tool that is the combination of adaptive filter and nonlinear sigmoid function, utilized to model saturation-type nonlinearity present in the acoustic systems [18]. In this technique, two different adaptive algorithms are utilized; first, conventional fixed-step-size (FSS)-LMS procedure is utilized to update the sigmoid parameters and second, conventional RLS procedure is utilized for estimation of coefficient vector of transversal filter. When information about audio/speech signal as well as noise data is unavailable *a priori*, it is quite difficult to design an adaptive algorithm for AEC. As the FSS-LMS algorithm is having slow asymptotic convergence rate, as discussed by Morgan in [22], which is also supported based on convergence analysis of LMS filter using uncorrelated input data by Feuer and Weinstein in [23].

In order to enhance tracking ability as well as convergence rate of simple FSS-LMS procedure, a robust-variable-step-size (RVSS)-LMS procedure is discussed by Kwong and Johnston in [24]. In this, the step-size value increases or decreases at each iteration depending upon the value of error signal at that time. To further enhance the convergence rate, another variable adaptive step-size procedure has been suggested by Aboulnasr and Mayyas in [25]. In this TMVSS-LMS procedure, the value of step-size increases or decreases at each iteration depending upon the value of autocorrelation between present error signal sample value and its previous sample value. These variable step-size procedures enhance convergence rate at the cost of increased steady-state error. Stochastic gradient adaptive filtering procedures utilizing VSSs have been investigated in [26]. To improve the tracking ability further more and make convergence rate even faster, many other version of LMS procedure have been reported in literature, like log-log LMS algorithm [27] and the LMS gradient adaptive step-size algorithm [28] etc. As we know, the aforementioned NAEC is using simple RLS procedure [19], [29], [30] for estimation of coefficient vector of general FIR filter, and its comparison has been done with simple NLMS procedure [17], [18], [19], [30] to show its advantages in terms of echo-return-loss-enhancement (ERLE). In order to decrease the misadjustment level further (of the above mentioned NAEC), many other versions of RLS and NLMS algorithms were presented like VSS-NLMS procedure for under-modeling acoustic echo cancellation [31], in which step-size of NLMS algorithm varies at each iteration depending upon the value of error signal; and the variable forgetting factor LS procedure for polynomial channel paradigm [32].

In [33], an adaptive procedure is detailed by Kohli and Mehra for tracking of time-variant channels. In this case, two-step LMS procedure is utilized, which exhibits more stable behaviour in time-varying environments akin to acoustic echo environment. In [34], for the fine tuning of the nonlinear sigmoid-type transformation function, a robust fixed point transformation technique was presented by Kosi *et al.* In this case, only single parameter (slope parameter) sigmoid-type function was utilized, which is widely accepted in engineering practices. Shynk studied the multirate adaptive filters in frequency-domain [35].

To boost the convergence speed of adaptive procedures, a method to apply particle-swarm-optimization (PSO) techniques in the generalized adaptive nonlinear and recursive filter structures is suggested in [36]. PSO is a population based optimization procedure, same as genetic-algorithm (GA), which governs a structured randomized search of an unknown parameter space by manipulating a population of parameter estimates for convergence to a satisfactory remedy. To check robustness of NAEC, different types of input signals can be fed to it, such as uncorrelated signal like Gaussian signal [37], correlated signals like AR(1) signal [38], [39] and AR(2) signal [30], [40], [41]. New strategies are developed and used nowadays like functional adaptive filters [42], in which nonlinear expansion of input signal is carried out. It enhances its representation through projection in higher-dimensional space. Subsequently, adaptive filtering kernel based Hammerstein systems for echo cancellation [43] and NAEC based upon linearly constrained affine projection algorithm [44] are proposed. In [45], a scheme utilizing adaptive Volterra kernels is discussed by Ruiz, which can be also utilized in case of NAEC. In [46], authors presented a technical review on adaptive algorithms used for acoustic echo cancellation. In [47], NAEC using voltage as well as current feedback technique was presented by Shah *et al.* In this technique, a simple elegant hardware modification in small smartphones significantly reduces nonlinear echo. Image technique has been studied by Allen and Berkley [48], in which variation of room impulse response due to thermal fluctuations and its effects on AEC are discussed in [49]. The room impulse response is generated, which is akin to the acoustic systems in [50]. Here, background noise is another significant issue [51], which needs to be cancelled. A version of adaptive filters is under development, which is sparse adaptive filter for echo cancellation [52]. Moreover, nowadays many new algorithms are used for updating and estimation purposes in NAECs [27], [36], [42], [53] in order to enhance performance in the presence of thermal variations, which affect the room impulse response significantly [48], [49], [50]. In [54], the performance characteristics of LMS adaptive filter composed of tapped-delay-line and adjustable weights are described by Widrow *et al.* The effect of noise in this case is expressed as dimensionless quantity i.e., misadjustment, which is a measure of deviation

from optimal Wiener performance. In [55], variable forgetting factor linear least squares procedure is reported by Song *et al.*, which is utilized to enhance tracking capability of the channel estimation. This method shows a remarkable improvement in fast fading environment. In [56], a convex combination of two transversal filters is explored. The individual filters are adapted independently by using error signals, while this combination is adapted by a stochastic gradient procedure in order to reduce the error of overall structure. In [57], to address the acoustic echo problem, Comminiello *et al.* introduced a nonlinear-acoustic-echo-cancellation (NAEC) structure based on an adaptive combination of linear as well as nonlinear filters. The algorithms and techniques used in NAEC application is not only limited to the acoustic systems, but these can also be used in noise cancellation approaches like noise removal from digital hearing aids [51], from the ECG signals [58], and from EEG signals [59].

## **1.2 STATEMENT OF PROBLEM BASED ON BRIEF LITERATURE REVIEW**

This thesis presents the following research work

The nonlinear acoustic distortion is inevitable under the large-signal situation in case of power amplifier and/or loudspeaker, which impairs the performance of linear acoustic-echo-cancellers (AECs). The nonlinear cone as well as uneven magnetic flux densities in the loudspeaker establish nonlinear distortion at the large cone displacement levels [10]. However, it is tedious to design a unified paradigm that can describe almost every type of nonlinear distortion. Adaptive nonlinear techniques are required to acquire adequate echo cancellation [10]. But, the performance of nonlinear-acoustic-echo-cancellers (NAECs) is highly dependent on the nature of echo path [18]. The linear AEC fails to perform well, when nonlinear echo paths come into picture. Therefore, NAECs have been explored to handle the loudspeaker nonlinearities [2] – [5], [12] – [16]. A nonlinear transform incorporating a variable saturation curve and adaptive finite-impulse-response (FIR) filter are investigated in [10] and [60]. But, it [10] leaves the shape of saturation curve non-adjustable, and it [60] is found to be acceptable for ideal hard-clipping distortion situation only.

A new class of nonlinear adaptive filtering configurations, whose architecture is dependent on Hammerstein paradigm, is presented in [42]. It exploits the nonlinear input expansion to utilize the functional link adaptive filtering, in which the linear and nonlinear adaptive elements are segregated using two different adaptive filters in parallel. In [43], an NAEC algorithm based on framework of kernel method is reported, in which a resource efficient strategy is utilized to identify the linear and nonlinear parts. But, its computational complexity limits its applications.

The nonlinear characteristics of loudspeaker are commonly modelled by using nonlinear polynomial, which can be approximated by utilizing the adaptive Volterra filtering/polynomial filtering [10]. A cascade of a polynomial and FIR filter can cancel nonlinear echo [60], which employs a hard-clipping curve with normalized-least-mean-square (NLMS) adapted saturation parameter and recursive-least-square (RLS) type adaptation for polynomial. In [8], first module is Volterra filter, which is equivalent paradigm for a loudspeaker with nonlinear distortion, and impulse response of acoustic path is modelled as a tapped-delay-line filter. Under practical situation, the loudspeaker nonlinearities are modelled quite well using the third-order Volterra filtering paradigm, which is an approximate choice for AEC. Though the second-order Volterra filter converges at higher rate, but echo-return-loss-enhancement (ERLE) is observed to be higher in case of third-order Volterra filter, when the generalized variable-step-size NLMS algorithm [7] is incorporated.

In [17], a nonlinear transformation dependent on raised-cosine function is utilized in conjunction with a traditional linear adaptive filtering configuration. The nonlinear transformation parameters are estimated using NLMS algorithm, which maps the nonlinear characteristics of a loudspeaker. This technique is capable to adapt to both soft-clipping as well as hard-clipping nonlinearities, and it outperforms Volterra filtering approach. When echo path is modeled by Volterra filter with unknown order, the performance of this method is comparable to adaptive Volterra filter in terms of ERLE. Its exclusive benefit/feature is low computational complexity, as only two parameters need to be updated for efficient implementation of this approach. However, the piecewise nature of nonlinear transform limits the detailing of convergence characteristics of this algorithm.

The NLMS and RLS algorithms can be used to eliminate the acoustic echo caused by linear echo paths (assuming linear room impulse response and nonlinear characteristics of the loudspeaker) [11]. When NLMS is used in AEC [31], the choice of step-size reflects a trade-off between fast convergence rate as well as good tracking capability on one side and low misadjustment [33] on other side. To accomplish these conflicting specifications, the step-size is required to be controlled [59]. In [10], a novel NAEC utilizes a sigmoid function followed by a traditional linear adaptive filtering configuration, in which the parameters of sigmoid function and tap-coefficient vector of adaptive filter are updated using LMS and RLS algorithms respectively. It exhibits low computational complexity and possesses high convergence rate in this echo cancellation technique, while combating the saturation-type nonlinear distortion of loudspeaker encountered in echo path. It supersedes the Volterra filtering approaches [4], [13], [19], when the echo path undergoes a saturation-type nonlinear distortion. One of the primary disadvantages of Volterra filtering is a large number of

parameters (it typically needs to characterize a nonlinear system) and the correspondingly high computational load needed to adapt such a large number of parameters. The parameter count in a Volterra expansion rises up exponentially with the order of nonlinearity. Moreover, these filters suffer due to their low convergence rate and high computational burden.

A cascade of linear AEC and nonlinear post-processor is presented in [44], which are updated using an affine projection algorithm and LMS algorithm respectively. Here, the hard-clipper as well as sigmoid function are considered for the post-processing. It handles the saturation-type nonlinear distortion of a microphone circuit. Though it provides stable and fast converging technique under zero system noise conditions, but its computational complexity precludes its usage. However in addition to system noise [31], the residual echo caused by the part of system (that can't be modelled) may be interpreted as additional noise. The performance of NLMS procedure operating in the nonstationary environment is also influenced by this noise and characteristics of input signal (uncorrelated Gaussian and correlated autoregressive (AR) process [40]). However, the thermal fluctuations in room affect the impulse response of loudspeaker or microphone, which can result in surprisingly large variations in the overall nonlinear echo path impulse response [49]. Therefore in this research work, we focus on the nonlinear acoustic echo cancellation utilizing adaptive algorithms under noisy environment, in which the parameters of sigmoid function (equivalent to the loudspeaker nonlinearity [18]) are updated using VSS-LMS algorithm [24], [25], [30], and the echo generated due to multipath transmission through static channel is estimated by using NLMS [8], [30] or RLS algorithms [6], [32].

### **1.3 ORGANIZATION OF THESIS**

This thesis is organized in following five chapters

Chapter 1, provides introduction about linear and nonlinear acoustic echo cancellers. The statement of problem is also discussed to carry out presented research work.

In Chapter 2, various adaptive procedures are discussed taking the view of acoustic echo cancellation in consideration.

In Chapter 3, nonlinear acoustic echo cancellation problem is handled using different adaptive approaches based on FSS-LMS, VSS-LMS, NLMS and RLS algorithms under ideal conditions.

In Chapter 4, we present an adaptive nonlinear echo cancellation approach, which is based on variable step-size LMS and RLS procedures. In this technique, nonlinearity of electronic

equipment is modelled and adaptively identified based on parameter estimation using VSS-LMS algorithm. However, the acoustic path is estimated by using RLS algorithm under noisy environment. The efficiency of presented NAEC is verified using simulation results, while considering the uncorrelated and correlated input signals.

Chapter 5, includes concluding remarks as well as future scope.

The performance evaluation of underlying NAEC scheme is conducted by using appraisal factors i.e., mean squared error and echo return loss enhancement based on Monte-Carlo simulation results (ensemble averaged).

## CHAPTER 2

# ADAPTIVE FILTERING ALGORITHMS

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*In this chapter, we highlight the desideratum of adaptive filtering configurations, their development, basic block diagram and various adaptive algorithms. Then, we focus on the acoustic systems and their biggest issue, which is the removal of nonlinear echo components from the output of these acoustic systems. We start with the traditional Volterra filter based AECs, their structure and implementation. Subsequently, we focus on the nonlinear acoustic echo path, which is main challenge to the echo cancellation systems. We investigate a few NAEC approaches to tackle nonlinearity present in acoustic systems. Finally, we investigate various problems and application areas of adaptive filters, and subsequently present a brief comparison between basic adaptive algorithms used for the enactment of adaptive filters.*

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### 2.1 INTRODUCTION TO ADAPTIVE FILTERS

Filtering in most common terms is a process of noise excision from a recorded process in order to reveal or improve information about some quantity of interest. Filters are classified as linear and nonlinear types. In the last decennary, the field of digital signal processing, and especially adaptive nonlinear signal processing, has seen tremendous development due to the increased availability of technology for the implementation of the emerging algorithms [19], [20], [29], [30], [37], [40]. These algorithms are used in various fields such as noise and echo canceling, channel equalization, signal prediction, adaptive arrays etc. Previously, different kinds of digital filters have been explored that are characterized as time-invariant. It means that filter coefficients remain fixed throughout the tenure of filter. An adaptive filter is designed such that the coefficients change with time in a strongly controlled manner, and this is achieved by using an adaptive algorithm. Linear filters have played a crucial role in the development of various signal processing techniques, and the main advantage is their simplicity. However, there may exist situations, in which the performance of linear filters may be unacceptable, and therefore, the need of nonlinear filters comes into the picture. Usually, adaptive filtering methods are used when it is tedious to understand the characteristics of signal. The extent of variation of the incoming signal is uncertain, which implies that the adaptive filter needs to adjust according to the attributes of input signal. A linear optimum discrete-time filter, called as Wiener filter [19], [30], processes the input signal by utilizing a discrete-time linear system, which provides an estimate of original signal at the output. Therefore, a system capable of removing the effect of noise is required. An

adaptive filter is a self-adapting digital filter that tunes its coefficients in order to minimize error function. This error function, also known as the cost function, is a difference measured between reference or desired signal and output signal of filter.

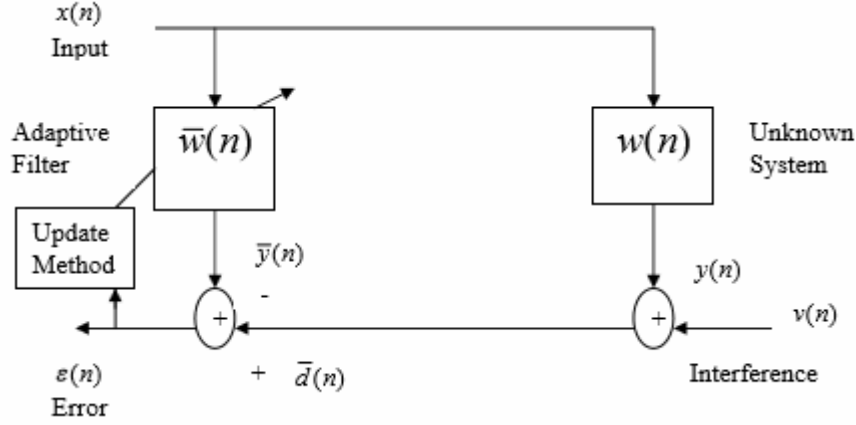


Figure 2.1 General adaptive filtering configuration [30]

The basic layout of adaptive filtering configuration, which is operating in discrete-time domain  $n$ , is illustrated in Figure 2.1. In this figure, input signal is denoted by  $x(n)$ , the signal  $y(n)$  denotes output of unknown system,  $\bar{d}(n)$  represents desired output signal. The output signal usually includes some noise component, which in this case is additive white Gaussian noise signal denoted by  $v(n)$ , such that

$$\bar{d}(n) = y(n) + v(n) \quad (2.1)$$

where,  $y(n)$  is output of unknown system, which is represented as

$$y(n) = x(n) * w(n)$$

where,  $\bar{y}(n)$  is the output of adaptive filtering configuration, and is evaluated as

$$\bar{y}(n) = x(n) * \bar{w}(n)$$

and the error signal is represented as

$$\varepsilon(n) = \bar{d}(n) - \bar{y}(n) \quad (2.2)$$

where,  $w(n)$  are weight vector coefficients of unknown system, and  $\bar{w}(n)$  are weight vector coefficients of adaptive filter. There are different adaptive algorithms, which are used to reduce the error signal, like the steepest-descent algorithms, least-mean-square (LMS) [17], [18], [30], normalized-least-mean-square (NLMS) [30], [40], recursive-least-square (RLS) [18], [29], [30] etc. The simplest of all algorithms is the LMS procedure. However, the performance of LMS procedure in terms of echo cancellation is lower than other adaptive filtering algorithms, because it has slow convergence rate and large misadjustment level.

Nevertheless, it is used in numerous applications of adaptive filters because it is easy to analyze.

In the area of adaptive signal processing, Wiener was first to develop adaptive filters popularly known as Wiener filter [19], and its optimal solution is known as Wiener solution. This solution acts as a benchmark for all other forthcoming adaptive filters in the area of signal processing.

## **2.2 ADAPTIVE FILTERING TECHNIQUES**

In several applications, the characteristics of the system under consideration are unknown. Adaptive signal processing is a methodology, where the adaptive model can be designed through an iterative method, so that the characteristics of the model best fit the unknown system. This model, which is always time-varying in nature, is called adaptive filter.

A general adaptive system configuration is shown in Figure 2.1. It mainly consists of

- a) Unknown system: It is characterized by the time-varying parameters.
- b) Adaptive filter: It is associated with the unknown system. It is based on iterative methodology. The input signal is passed through this block to generate an error signal at output, which is utilized to determine update method.
- c) Update method: It is the basic methodology behind the adaptive system. It determines the traits of adaptive filtering configuration, which is based on nature of unknown system. It usually involves a number of mathematical operations and expressions. There are various update methods used in adaptive systems, such as LMS, NLMS, RLS algorithms etc.

Linear adaptive filtering configurations are utilized in acoustic echo cancellers and many other applications because of their global convergence and stability.

## **2.3 STEEPEST DESCENT ALGORITHM**

It is an algorithm for searching nearest local minima of the function, which surmises that the local minima of function can be computed by using the gradient of function. The method of steepest-descent (SD) [19], also called the gradient descent method is an algorithm, which can be considered as efficient gradient-type procedure that updates weight vector at each iteration step.

Actually, it is an algorithm to find the local minima of a function. The most important factor in this algorithm is the choice of step-size. A fallacious step-size may not reach convergence, so a precise selection of the step-size is important. If its value is large, it will diverge and will converge if the value of step-size is small. One option is to choose a fixed

step-size that will assure convergence, where a researcher should start gradient descent; and another way is to choose adaptive step-size for each iteration, which is called adaptive step-size, and this technique is used in the variable least mean square algorithms.

### 2.3.1 Adaptive Step-size Algorithm

There are methods, known as line search, which estimate the value of the step-size at a given iteration [24], [25], [32], [44], [61], [62]. After evaluating the gradient, these methods choose step-size by minimizing the error function. Each method defines its own function, based on some assumptions. Exact methods accurately minimize the error function, while inexact methods make an approximation that just improves on the last iteration.

The SD procedure updates coefficients of filter in following general manner

$$\bar{w}(n+1) = \bar{w}(n) - \frac{1}{2} \mu g(n) \quad (2.3)$$

where,  $\mu$  is step-size of the SD algorithm, and  $g(n)$  is gradient vector coefficient at time 'n'. It is worth-noting that several alternative gradient-based algorithms are available, in which  $g(n)$  is replaced by  $\hat{g}(n)$ , which depends upon how a gradient vector is estimated.

## 2.4 DIFFERENT TYPES OF ALGORITHMS USED IN ADAPTIVE FILTERS

In adaptive nonlinear filters, there are a number of algorithms, which are used in order to minimize the error signal or cost function of filter and many more are still under progress. These algorithms are used to depreciate the difference between the actual output of filter and desired output of filter in order to attain the desired output by minimizing the filter coefficients. This is because, as number of filter coefficients increases, its cost and complexity also increases. Therefore, the main motive in adaptive filter designing is to reduce the number of filter coefficients. There are various number of adaptive filter algorithms, which are different and better than previous class of procedures in terms of mean squared error estimation and convergence behaviour, but here we discuss only few of them, which form the basis for all the rest adaptive filter algorithms. Basically, truncated Volterra series is used in adaptive nonlinear filters designing, which is given as

$$\bar{y}(n) = \sum_{n=0}^{N-1} \bar{w}_1(m_1)x(n-m_1) + \sum_{n=0}^{N-1} \sum_{n=0}^{N-1} \bar{w}_2(m_1, m_2)x(n-m_1)x(n-m_2) + \dots + \sum_{n=0}^{N-1} \dots + \sum_{n=0}^{N-1} \bar{w}_p(m_1, m_2, \dots, m_p)x(n-m_1), \dots, x(n-m_p) \quad (2.4)$$

where, the order of the filter is  $p$  and  $N$  is number of iterations.

#### 2.4.1 Least Mean Square Algorithm

Least mean square algorithm [19], [30] is simplest procedure utilized in adaptive filters in order to reduce the error signal of adaptive filter. It is a stochastic gradient descent scheme, in which filter is only adapted based on error at current time. This procedure updates coefficients after each iteration using steepest descent algorithm, which tries to minimize square of error signal at end of each iteration. Least-mean-square (LMS) procedure is widely utilized adaptive filtering technology. The wide range of applications of LMS procedure can be attributed to its simplicity and robustness to signal statistics. The key idea behind LMS algorithm is to achieve optimal filter weights by updating filter weights in a specific trend. In the beginning, this procedure assumes small values of weights ('0' in most cases), and the weights are updated at each step by finding the gradient of mean-squared-error (MSE), which implies that if MSE gradient is positive, it indicates that error would keep rising positively, and hence there is a requirement to reduce weights. In the same way, if gradient is negative, the weights are required to be increased. So, weight update equation may be expressed as

$$\bar{w}(n+1) = \bar{w}(n) + \mu_F E[\varepsilon(n)(\varepsilon'(n))^*] \quad (2.5)$$

where,  $E[\varepsilon(n)(\varepsilon'(n))^*]$  represents the mean squared error,  $E[.]$  denotes the expectation operation, and  $\mu_F$  represents the step-size used for the algorithm. The convergence coefficient of the filter and its matrix consists of quadratic as well as linear values, both for recursive and non-recursive systems. The negative sign implies that we require to vary weights in a direction opposite to that of gradient slope. The MSE, is a quadratic function of filter weights, which means it has only one extreme value that minimizes the MSE, and hence a favorable weight value is achieved. The LMS algorithm approaches towards the optimum weights by increasing or decreasing MSE as per requirement. In present era, various versions of LMS algorithm are developed, in which step-size of the algorithm is made adaptive in nature, in order to increase efficiency of LMS algorithm [24],[25], [27].

#### 2.4.2 Normalized Least Mean Square Algorithm

The main shortcoming of LMS procedure is that it is sensitive to scaling of its input. This makes it very hard to select a learning rate  $\mu_N$  i.e., step-size that assures stability of procedure. The normalized least mean square procedure [19], [30] is a variant of the LMS

procedure that solves this issue by normalizing power of input. It can be demonstrated that, if there is no intervention then optimum learning speed for NLMS algorithm is dependent on  $\mu_N$ , which is step-size for NLMS algorithm and is independent of input as well as real (unknown) room impulse response. In common case, when the interference is not equal to 0, the optimal learning rate is

$$\mu_N = \frac{E[|y(n) - \bar{y}(n)|^2]}{E|\varepsilon(n)|^2} \quad (2.6)$$

where,  $y(n)$  is output of unknown system,  $\bar{y}(n)$  is output of filter and  $\varepsilon(n)$  is error signal. In NLMS, step-size is normalized to overcome the problem of gradient noise amplification. The update equation for NLMS algorithm is

$$\bar{w}(n+1) = \bar{w}(n) + \mu_N \frac{(\varepsilon(n))^* x(n)}{x^T(n)x(n)} \quad (2.7)$$

$x^T(n)$  represents transpose of the input signal vector, if input signal is real only. Many other improvements in NLMS algorithm are under consideration in order to increase its convergence rate [31], [40].

### 2.4.3 Recursive Least Square Algorithm

The recursive-least-square (RLS) adaptive filter is a procedure [19], [29], [30], which recursively finds filter coefficients that minimize a weighted linear least squares cost function associated with input signals. The RLS procedures are known for their remarkable performance, when working in time-varying scenarios, but at the cost of an increased computing entanglement and a few stability issues. In this procedure, the filter weight vector is updated by the usage of following equations

$$\bar{\bar{w}}(n) = \bar{\bar{w}}(n-1) + e_{pri}(n) \bar{\bar{R}}_D(n) \bar{x}(n) \quad (2.8)$$

$$e_{pri}(n) = \bar{d}(n) - \bar{x}^T(n) \bar{\bar{w}}(n-1) \quad (2.9)$$

$$\bar{\bar{R}}_D(n) = \frac{1}{\lambda_R} \left[ \bar{\bar{R}}_D(n-1) - \frac{\bar{\phi}(n) \bar{\phi}^T(n)}{\lambda_R + \bar{\phi}(n) \bar{x}(n)} \right] \quad (2.10)$$

where,  $\lambda_r$  (forgetting factor) is smaller than unity,  $x(n)$  is input signal vector, which is real in nature and  $e_{pri}(n)$  is the *a priori* error signal, which estimates RLS algorithm stability. The performance of this algorithm depends upon this estimation and  $\vec{R}_D(n)$  is evaluated as

$$\vec{R}_D(n-1) = \delta \vec{I}$$

where,  $\vec{I}$  is identity matrix and  $\delta$  is constant determining the initial matrix and  $\vec{\phi}(n)$  is represented as

$$\vec{\phi}(n) = \vec{R}_D(n-1)\vec{x}(n)$$

In RLS procedure, estimate of previous samples of output signal, error signal and filter weight are needed, which demands memory. In order to decrease the misadjustment level and increase the convergence rate of this simple RLS algorithm, other versions of RLS algorithm have been developed [32] and used in various adaptive field applications.

## 2.5 ACOUSTIC ECHO CANCELLATION SYSTEM

The common setup for acoustic-echo-cancellation (AEC) is depicted in Figure 2.2. The received far end speech is the output at near-end loudspeaker, passing through loudspeaker enclosure microphone system to cause echo signal. Most AEC designs seek to suppress the acoustic echo by reconstructing and subtracting the estimate of echo signal from the microphone-received signal. Historically, under the consideration of a completely linear acoustic chain (involving a power amplifier, loudspeaker, room impulse response, and microphone), a number of adaptive procedures based on gradient theory were developed to eliminate echoes, while keeping full-duplex communication features intact. Because of simplicity, normalized-least-mean-square (NLMS) algorithm [19], [30], [40] represent a famous method for AECs. However, NLMS procedure suffers from low convergence for correlated input signals. Therefore, more sophisticated procedures with decorrelating capability, such as affine projection procedure or recursive least square procedure [19], [29], [30] have been presented to speed up adaptation of filter coefficients.

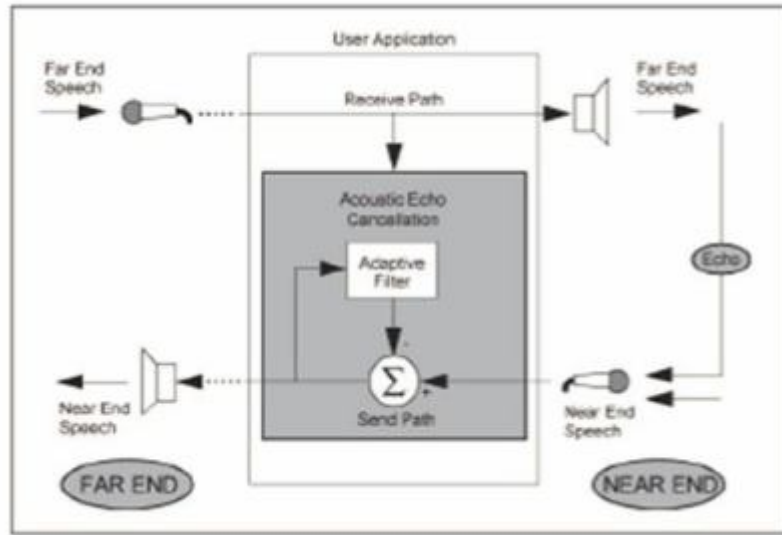


Figure 2.2 General acoustic echo canceller [30]

Consequently, low-complexity techniques that exploit the fast block convolution schemes in the discrete-Fourier-transform (DFT) domain have been introduced to relieve the computational burden. For example, adaptive DFT-domain procedures of constrained as well as unconstrained types are developed. In these schemes, time-domain linear convolution (utilized for filtering) and linear correlation (utilized for adaptation) are efficiently incorporated in frequency-domain utilizing overlap-save procedure. However, algorithm of data gathering might introduce a long delay. This inherent delay of the order of few hundreds milliseconds for typical room acoustic scenarios, is intolerable, as it prevents a natural, full-duplex speech conversation.

### 2.5.1 Volterra Filter Based AECs

The Volterra-filter (VF) has been widely considered as a nonlinear adaptation in AEC [3], [4]. It is a truncated version of Volterra series with finite memory as well as finite order. The block diagram of general filter using the truncated Volterra series is shown in Figure 2.3. Given an input signal  $x(n)$ , the output of a nonlinear system as Volterra series is nonlinear in nature; using  $k^{th}$ -order VF can be represented as

$$\bar{y}[n] = \sum_{i_1=0}^{N_1-1} \bar{w}_1(i_1)x(n-i_1) + \sum_{i_1=0}^{N_2-1} \sum_{i_2=0}^{N_2-1} \bar{w}_2(i_1, i_2)x(n-i_1)x(n-i_2) + \sum_{i_1=0}^{N_k-1} \dots \sum_{i_k=0}^{N_k-1} \bar{w}_k(i_1, \dots, i_k)x(n-i_1)\dots x(n-i_k) \quad (2.11)$$

where,  $\bar{w}_1(i_1)$ ,  $\bar{w}_2(i_1, i_2)$ ,  $\bar{w}_k(i_1, \dots, i_k)$  are the coefficients of adaptive filter, and  $N_k$  is the memory of the  $k^{th}$ -order kernel of the VF. Actually, Volterra kernels are usually assumed to be symmetric, which means  $\bar{w}_2(i_1, i_2) = \bar{w}_2(i_2, i_1)$  for 2<sup>nd</sup>-order VF.

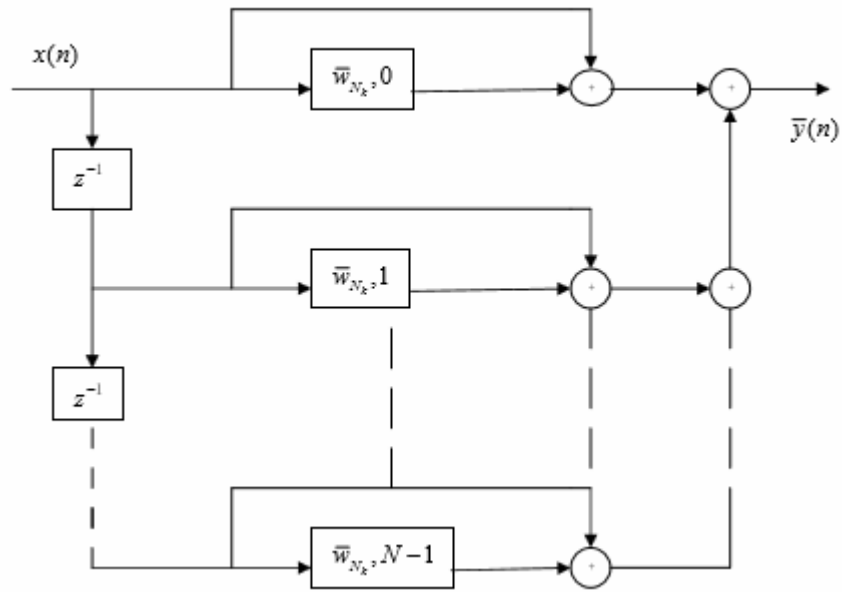


Figure 2.3 General Volterra series based filter [4]

The basic block diagram of acoustic echo canceller based on the Volterra series based filter is given in Figure 2.4.

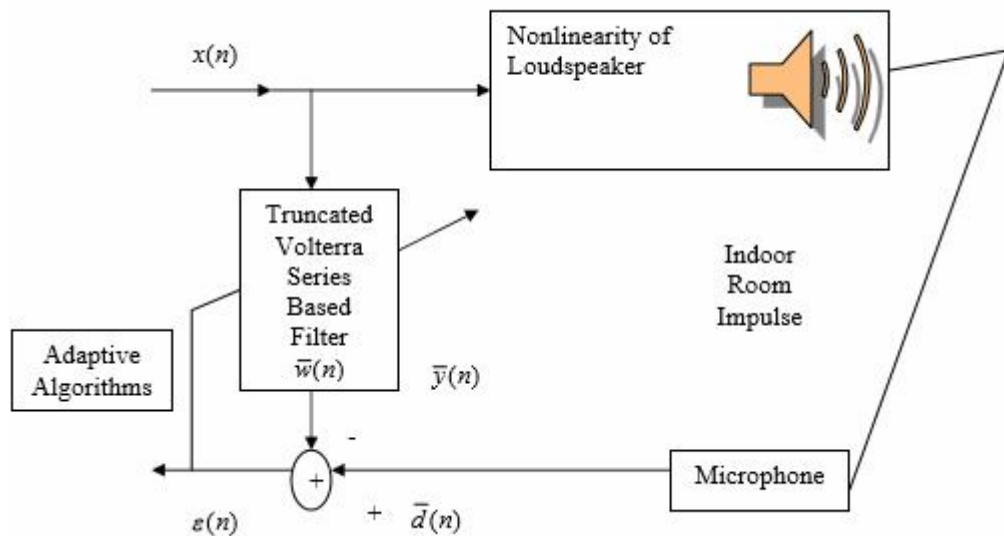


Figure 2.4 General Volterra series based AEC [2]

In this block diagram of basic acoustic echo canceller based on the Volterra series based filter, the input  $x(n)$  is given to both loudspeaker (which act as an unknown system in this case) and to truncated Volterra series based filter,  $\bar{d}(n)$  is the output of system after passing input through loudspeaker and indoor room impulse response and  $\bar{y}(n)$  is the output of Volterra series based filter, whose filter coefficients are denoted by  $\bar{w}(n)$ . In the Figure 2.4, the error signal is denoted as  $\varepsilon(n)$ , and depending upon this error signal the adaptive

procedures akin to LMS, NLMS, RLS etc. are utilized in the Volterra series based filter in order to update its filter coefficients i.e.,  $\bar{w}(n)$ .  $\bar{d}(n)$  and  $\bar{y}(n)$  best match with each other to give lowest possible error signal.

## 2.6 NONLINEAR ACOUSTIC ECHO CANCELLATION

There are numerous types of nonlinearities observed in electronics additives that are utilized in telecommunication engineering, which degrade the performance of acoustic systems. Particularly, the nonlinearity of amplifiers and/or loudspeakers offers upward drift to nonlinear echo in the acoustic structures, which severely deteriorates the performance of speech and audio communications. Linear echo components, which are present in acoustic systems, may be removed without any problem with the help of linear acoustic echo cancellers, but the nonlinear echo can not be disposed off by using linear acoustic echo canceller. To get rid of those nonlinear components, the nonlinear acoustic echo canceller comes into existence. Many nonlinear-acoustic-echo-cancellation (NAEC) techniques [4] – [18] have been presented till date.

A recent fashion in consumer electronics is to utilize low-cost as well as small-sized analog components (such as loudspeakers) for economic considerations. These components generally exhibit nonlinear features, and therefore, the dependence on powerful signal processing procedures to mitigate distortions has highly increased. The nonlinearities in acoustic systems are roughly divided into two kinds: nonlinearity with and without memory. Nonlinearity with memory generally occurs in high-quality audio devices, when time constant of loudspeaker's electromechanical system is large as compared to sampling rate [4]. Memoryless nonlinearity typically occurs in the low-cost power-amplifier (PA) or loudspeaker of mobile equipment, where weight constraints call for low supply voltages [12], [60].

Nowadays, to get rid of these nonlinear echo components, a simple method is utilized in acoustic echo cancellers, wherein in conjunction to adaptive transversal filters a nonlinear remodel characteristic is used, which represents the nonlinearities of loudspeakers and/or amplifiers and make parameters self-adjustable to nonlinearities of these electronic instruments. Hence, they smoothly cancel the impact of these nonlinear components in acoustic and telecommunication systems. There is a huge wide variety of nonlinear rework functions used for this motive, some of them are spline nonlinear transformation function, raised-cosine transformation function [17], logarithmic transformation function, sigmoid-type nonlinear transformation function [18] and many more nonlinear transformation functions.

The block diagram of basic nonlinear acoustic echo canceller is shown in Figure 2.5. In this block diagram, the output of unknown system (which consists of loudspeaker, room impulse response, and microphone) is given as  $\bar{d}(n)$ , the output of Volterra series or nonlinear transform block is  $f(n)$ , obtained by passing input signal  $x(n)$  through it. This nonlinear transform block consists of a nonlinear function, which is used to map the nonlinearity of loudspeaker, so that it can remove echo components, which are nonlinear in nature at the output of acoustic systems. The output of general FIR filter is denoted by  $\bar{y}(n)$  and the error signal is given as follows

$$\varepsilon(n) = \bar{d}(n) - \bar{y}(n)$$

Depending on this error signal, various adaptive algorithms are used in order to estimate the coefficient vector of general FIR filter and for updating parameters of Volterra series or nonlinear transform function, which are used in turn to map the nonlinearity of loudspeaker exactly. This is done, so that the nonlinear echo components can be removed from the acoustic system output to some extent, which could not be achieved by using linear acoustic echo cancellers.

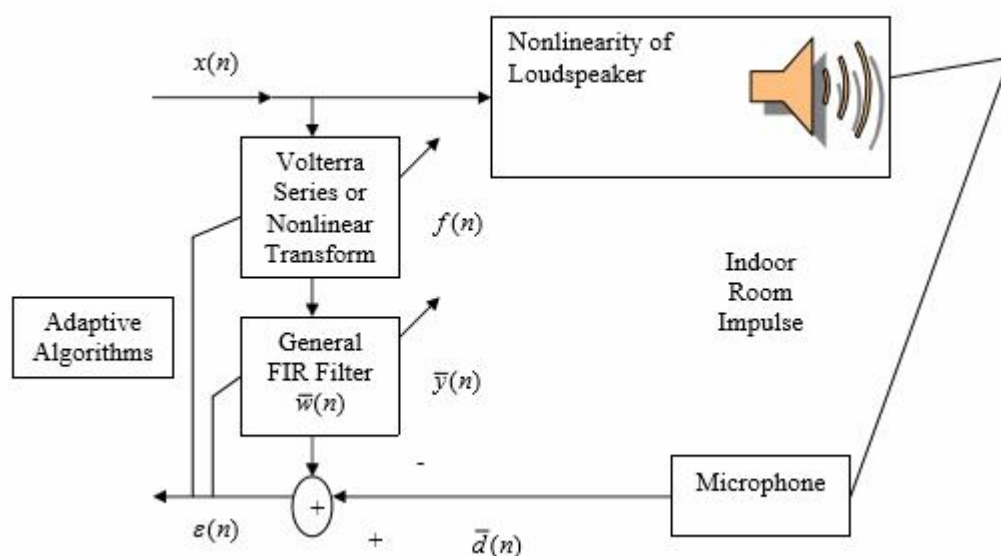


Figure 2.5 General nonlinear acoustic echo canceller [17]

### 2.6.1 Nonlinear Transform Based Acoustic Echo Cancellation

The memoryless nonlinearity is basically a type of nonlinear distortion, and an example of this is the saturation curve of loudspeakers and amplifiers. This mainly occurs in power amplifiers, in which echo path can be modelled by using a saturation-type nonlinear transform. This nonlinear transformation function helps to compensate the nonlinear distortion due to power amplifier used in conjunction with general FIR filter.

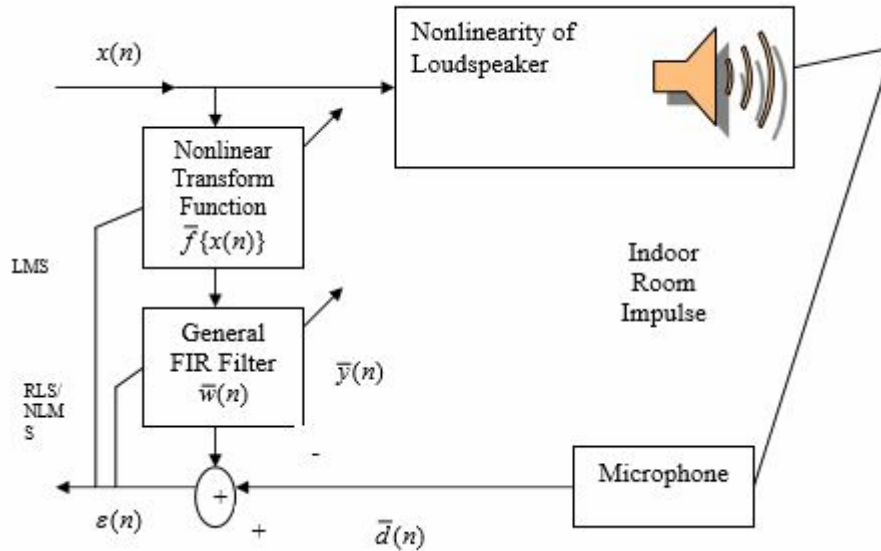


Figure 2.6 General nonlinear transform based acoustic echo canceller [18]

In this block diagram of general nonlinear transform based AEC, similar procedure is followed as simple nonlinear AEC. The only difference lies in Figure 2.6 as compared to Figure 2.5 is the nonlinear transform function block, which is added in case of nonlinear transform based AEC, and this is used to compensate the nonlinear distortions that occur due to the saturation-type nonlinearity of loudspeakers and/or amplifiers. The parameters of these nonlinear transformation functions are made adaptive to nonlinearities of these gadgets, so that may cancel the impact of these nonlinear components in acoustic and telecommunication systems. Nowadays, there is a huge wide variety of nonlinear transformation functions used for this motive, some of them are spline nonlinear transformation functions, raised-cosine transformation function [17], logarithmic transformation function, sigmoid-type nonlinear transformation function [18] and many more nonlinear transformation functions. Sigmoid is most general and easy to handle nonlinear transformation function, and NAEC based upon this transformation function is discussed in the subsequent chapters.

In summary, the nonlinear transform based acoustic echo cancellation methods are very efficient in dealing with such saturation-type nonlinearities. Furthermore, they exhibit a very low computational complexity as compared to VF-based AECs, and they are simple to handle.

## 2.7 ADAPTIVE FILTER PROBLEMS

- ❖ Quantity of interest not known - The quantity of interest in case of adaptive filters is the desired response of the system i.e.,  $d(n)$ . In practical applications, the

output of system is  $y(n)$ , which is a combination of  $d(n)$  and error  $e(n)$ . Some computations are performed by using input  $x(n)$ ,  $d(n)$  and  $e(n)$ .

- ❖ Quantity of interest not available at all times - For adaptation,  $d(n)$  should be available at all times, but in practical situations, it may be possible that all times it is not available. Then by using most recent parameter estimation output of the system is computed, such that it is approximately equal to desired response of the system.
- ❖ Quantity of interest never available - There are real world situations, when desired response of the system i.e.,  $d(n)$  is never available. In that case, blind adaptive algorithms are used, in which additional data about features of a hypothetical  $d(n)$  are used, which is predicted from the statistical behaviour or amplitude features to form appropriate estimates.

## 2.8 APPLICATIONS OF ADAPTIVE FILTERS

The different applications of adaptive filters are given below

- ❖ System identification - In this, higher-order system identification is performed using low order recursive adaptive filters taking advantage of their recursive properties.
- ❖ Channel identification - The adaptive filters are utilized to model the effects of channel inter-symbol interference for the purpose of deciphering the received data in an optimum way.
- ❖ Echo cancellation for long distance transmission – The impedance mismatch between the transmission lines and hybrid boxes near end of the links produces echo. This problem is solved with help of adaptive filtering, which is incorporated at each of the two hybrids within network.
- ❖ Adaptive noise cancelling – In this case, adaptive filters are used to nullify the effect of that noise, which is not always constant or in other words, highly random in nature. Adaptive filters are used to remove this kind of noise very accurately. Due to this property of adaptive filters, it finds applications in the medical field like ECG, hearing aide etc.

## 2.9 REVIEW OF ADAPTIVE FILTER ALGORITHMS

There are many algorithms used in adaptive filters in order to minimize the error between actual system output and desired filter output. They differ from each other on the basis of the complexity, cost, accuracy, stability and computational speed. Out of all these algorithms, LMS algorithm is the simplest algorithm, and widely used, although its accuracy and stability is very poor. Recursive least square algorithm is the most stable and accurate algorithm, but at the cost of increased complexity. NLMS has properties in between above two mentioned algorithms. So depending upon the applications, sensitivity and requirement of the application, any of the above algorithm of adaptive filters can be used for medical applications. RLS with sparse coefficients algorithm is frequently used because of its increased accuracy. The performance criteria of above three mentioned algorithms is given in Table 2.1, where M is the order of filter.

S.No	Algorithm	Stability	Complexity
1.	Least mean square	Less stable	$2M+1$
2.	Normalized least mean square	Moderate stable	$3M+1$
3.	Recursive least square	Highly stable	$4M^2$

Table 2.1 Stability and Complexity Comparison of Basic Adaptive Algorithms [19]

# CHAPTER 3

## CONVENTIONAL NONLINEAR ACOUSTIC ECHO CANCELLATION SCHEME WITH DIFFERENT TYPES OF INPUT SIGNALS

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*In this chapter, we present a detailed study on the performance criterion for nonlinear acoustic echo canceller, which uses nonlinear sigmoid transformation function in conjunction with tapped-delay-line filter to remove the nonlinear constituents of the acoustic echo, which can't be removed only by using linear acoustic echo cancellers. We firstly consider the structure of traditional NAEC, which is using nonlinear sigmoid transformation function and its behaviour, when we change its parameters. Secondly, we discuss adaptive algorithms used for updating sigmoid parameters, and then the adaptive procedures are utilized for estimation of tap-coefficient vector of tapped-delay-line filter. Later, we focus on the echo-return-loss-enhancement (ERLE) performance of NAEC and its comparison with linear NAECs using both uncorrelated and correlated input signals. After this comparison, analysis of different types of LMS algorithms utilized for updating the parameters of nonlinear transformation function of NAEC is conducted.*

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### 3.1 NONLINEAR ACOUSTIC ECHO CANCELLER

A linear adaptive filtering configuration filters a sequence of input data by controlling its tunable parameters via an adaptive procedure, which efficiently removes nonlinearities that arises in almost all the systems. Firstly, nonlinearities arises in telephone systems due to inaccuracies in signal companding. In order to remove these, nonlinear filters have been developed. The concept of nonlinear filters was first introduced by Wiener, a communication engineer, and he developed the first nonlinear filter, known as Wiener filter [19], [20], [30]. Since then many models were used for developing nonlinear filters, which include order statistics filters, homomorphic filters, morphological filters and the filters based on Volterra series. These nonlinear filters are used in speech enhancement, image enhancement, echo cancellation, noise cancellation, performance analysis of data transmission systems as well as in medical applications. The main thing that engendered the idea for developing nonlinear filters even while having linear filters, which had low complexity as well as performed satisfactorily, is the saturation-type nonlinearity, which is present in almost all types of electronic and electrical systems. The main type of nonlinearity present in the systems is the saturation-type of nonlinearity [17], [18]. This nonlinearity of electronic devices boosts

nonlinear echo in acoustic systems, which appreciably deteriorates overall performance of speech as well as audio reception. However, as the order of nonlinear filter increases, its complexity also increases exponentially and this poses another problem. Therefore at this stage, recursive systems come into picture [1]. The identification of higher-order systems is incorporated by using second-order recursive systems [2].

Dai and Zhu have presented an acoustic-echo-cancellation (AEC) technique, which uses raised-cosine feature [17] in a notable way to remove the nonlinearity of loudspeakers present in acoustic systems. In this case, raised-cosine function acts as an adaptable nonlinear transformation function, which is used to filter out the nonlinear echo components that arise in acoustic systems due to amplifiers and/or loudspeakers present in these systems. The fundamental issue, that arises in signal processing structures, is echo in the acoustic systems. In order to eliminate this nonlinearity, the adaptive filters are used. Fu and Zhu have presented a tool that is the combination of general transversal adaptive filter and nonlinear sigmoid transformation function [18], which is able to reduce the echo. In this NAEC, a transversal filter is used along with the nonlinear transformation function. In this case, the sigmoid transformation characteristic is used, which can incorporate any nonlinear transformation function reported in the literature. As information of signal as well as noise attributes are not available *a priori*, it is feasible to enhance the benefits of filter by utilizing recursive set of policies in order to modify the filter parameters, which are distinctly based on the input signal attributes. This is the prime purpose of adaptive filter. To revise the parameters of the sigmoid feature, various adaptive algorithms can be used. If signal as well as noise records are available, then adaptive filtering configuration is probably expected to ultimately converge to well known optimal Wiener solution. If they are not available, then filter tracks them at reasonably slow speed. However, coefficient vector of filter is estimated continuously according to information signal that passes through it.

### **3.2 NONLINEAR SIGMOID TRANSFORMATION FUNCTION**

Most of the time, researchers focus on the following points, when choosing the activation or transformation function

- Continuity of the function
- Computational power to process all neurons of the network
- Type of the desired output (logistic/continuous variables or classification/categorical data)

The sigmoid function offers all these characteristics, and it is easy to handle. Moreover, the sigmoid transformation function is akin to the saturation curve of the loudspeaker and/or amplifiers, which is the main source of nonlinearities. To remove these, which is the basic requirement, this curve is made adaptable by using various adaptive procedures. In neural networks, an activation function of a node operates on an input or a number of inputs and provides output in accordance to activation function features. A computer chip circuit may be realized as a digital network of activation functions that may be in "ON" (1) or "OFF" (0) state depending upon the input. It is akin to the behaviour of linear perceptron in neural networks. However, it is nonlinear activation function that permits such networks to solve nontrivial problems by utilizing less number of nodes. In artificial neural networks, this function is also called transfer function (not to be confused with a linear system's transfer function). In the field of artificial neural networks, the sigmoid function is a type of activation function for artificial neurons.

The most basic activation function is the Heaviside (binary step, 0 or 1, high or low). The sigmoid function is a special case of the logistic function.

Any researcher can have several types of activation functions, and these may be best suitable for different purposes. The basic characteristics of sigmoid function are

- Real-valued and differentiable
- Analytic tractability for the differentiation operation
- It is an acceptable mathematical representation of biological neuron behaviour. The output depicts whether the neuron is firing or not. In case of neuron, the input samples can also be considered

The basic equation of the sigmoid function used in this research work is given as

$$f(x) = \frac{2\hat{\beta}}{1 + e^{(-\hat{\alpha}x)}} - \hat{\beta} \quad (3.1)$$

where,  $x$  is the input given to NAEC as well as loudspeaker.  $\hat{\alpha}$  and  $\hat{\beta}$  are the two parameters of the sigmoid nonlinear transformation function.  $\hat{\alpha}$  determines shape of the saturation curve of the loudspeaker and  $\hat{\beta}$  determines clipping value of saturation curve. By changing values of these two parameters of sigmoid function, shape as well as clipping value of saturation curve of loudspeaker or amplifier can be varied. It means that by varying the sigmoid parameter values of sigmoid-type nonlinearity, the shape as well as clipping value of saturation-type nonlinearity of loudspeaker may be mapped.

### 3.3 CONVENTIONAL NAEC USING SIGMOID TRANSFORMATION FUNCTION AS NONLINEAR TRANSFORMATION FUNCTION

In this dissertation, a simple but efficient conventional nonlinear echo cancellation method is discussed [17], [18], as shown in Figure 3.1. In this conventional NAEC, an adaptable sigmoid characteristic is utilized alongside a tapped-delay-line filter. This scheme can make use of numerous types of LMS algorithms for updating parameters of sigmoid features and the RLS and/or NLMS procedure to estimate the coefficient vector of tapped-delay-line filter. This efficient nonlinear echo cancellation scheme with low complexity utilizes an adaptable sigmoid functional unit together with tapped-delay-line filter. This sigmoid transform is used to cancel the effect of nonlinearities of amplifiers and loudspeakers. The advantage of sigmoid transform is that it can adapt its parameters for both hard as well as soft clipping nonlinearities, and shows improved overall performance as compared to Volterra series based filters [1]-[4]. The simple equation of sigmoid-type characteristic is given in Equation (3.2), which is as follows

$$f\{x(n)\} = \frac{2\bar{\beta}}{1 + \exp(-\bar{\alpha}x(n))} - \bar{\beta} \quad (3.2)$$

where,  $x(n)$  is the input given to NAEC as well as loudspeaker.  $\bar{\alpha}$  and  $\bar{\beta}$  are the two parameters of the sigmoid nonlinear transformation function.  $\bar{\alpha}$  determines shape of the saturation curve of the loudspeaker and  $\bar{\beta}$  determines clipping value of the saturation curve. The idea is to update two parameters of sigmoid function by usage of the FSS-LMS and various versions of VSS-LMS algorithms. Subsequently, the unknown nonlinear distortion of the amplifier or/and loudspeaker is perfectly matched, and then cancelling nonlinear constituents of echo, which can't be cancelled by using linear acoustic echo cancellers. There are numerous adaptive algorithms used for updating the sigmoid feature parameters and for estimating the tapped-delay-line filter coefficient vector. The adaptive procedures utilized for this motive in this dissertation are as following. The Equation (3.2) represents the sigmoid-type nonlinearity for actual case; and for adaptive case, the sigmoid-type nonlinearity equation is given as

$$\zeta\{x(n)\} = \frac{2\tilde{\beta}_n}{1 + \exp\{-\tilde{\alpha}_n x(n)\}} - \tilde{\beta}_n \quad (3.3)$$

where,  $x(n)$  is the input given to NAEC as well as loudspeaker, and may be written as

$\bar{x}(n) = [x(n), x(n-1), \dots, x(n-M+1)]^T$ . Here,  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  are the parameters of sigmoid function, which are tracked by using various VSS-LMS procedures. When  $\tilde{\alpha}_n \rightarrow \bar{\alpha}$  and  $\tilde{\beta}_n \rightarrow \bar{\beta}$ , then  $\zeta \rightarrow f$ .

Here,  $f$  is same as in Equation (3.2).

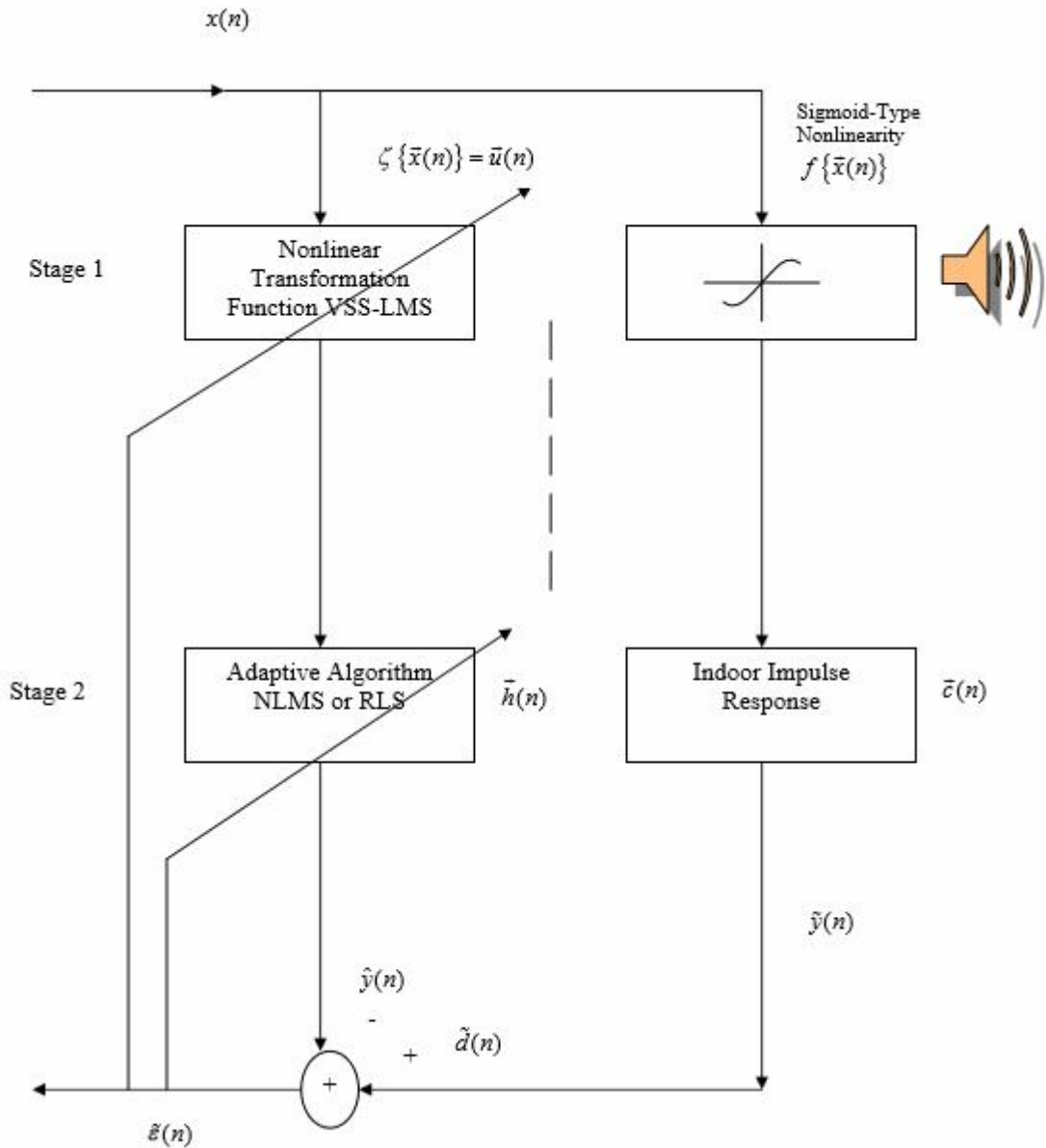


Figure 3.1 Conventional nonlinear acoustic echo canceller

$\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  are the two parameters of the sigmoid function in adaptive case as indicated in Equation (3.3), which are tracked by using various LMS algorithms one by one. We can change the shape as well as clipping value of saturation curve of loudspeaker by varying the values of parameters of sigmoid function. The idea is to update two parameters of sigmoid function by usage of FSS-LMS and various versions of VSS-LMS algorithms, so that unknown nonlinear distortion of amplifier or/and loudspeaker is impeccably matched, thereby

cancelling nonlinear constituents, which are present in the echo path and can't be tackled by using linear acoustic echo cancellers.

The figures given below show the sigmoid function characteristics and its behaviour, when its parameters are varied. The graphs of the sigmoid-type nonlinearity by varying the values of sigmoid parameters plotted by using MATLAB are presented in the following figures.

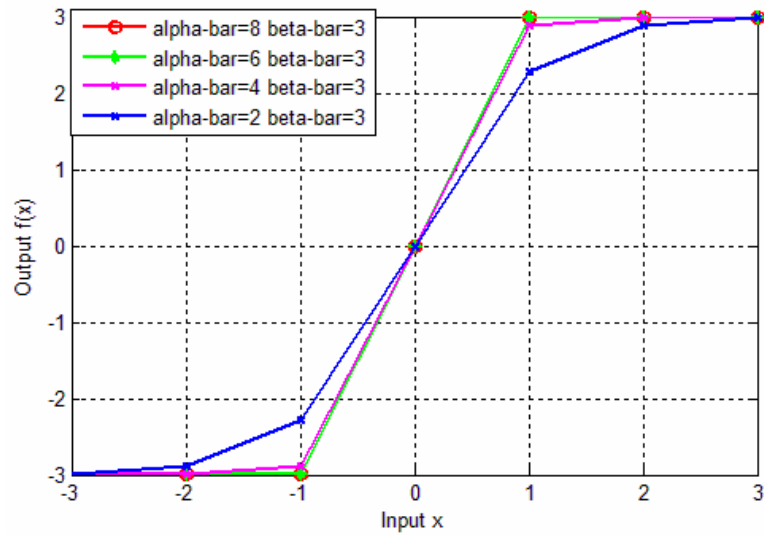


Figure 3.2.1 Nonlinear sigmoid transformation characteristics by varying the value of the shaping parameter of sigmoid function  $\bar{\alpha}$

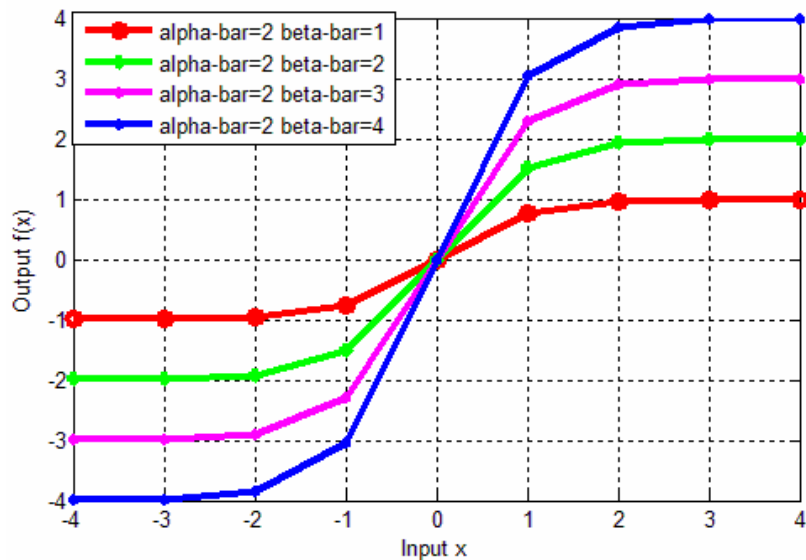


Figure 3.2.2 Nonlinear sigmoid transformation characteristics by varying the value of the clipping parameter of sigmoid function  $\bar{\beta}$

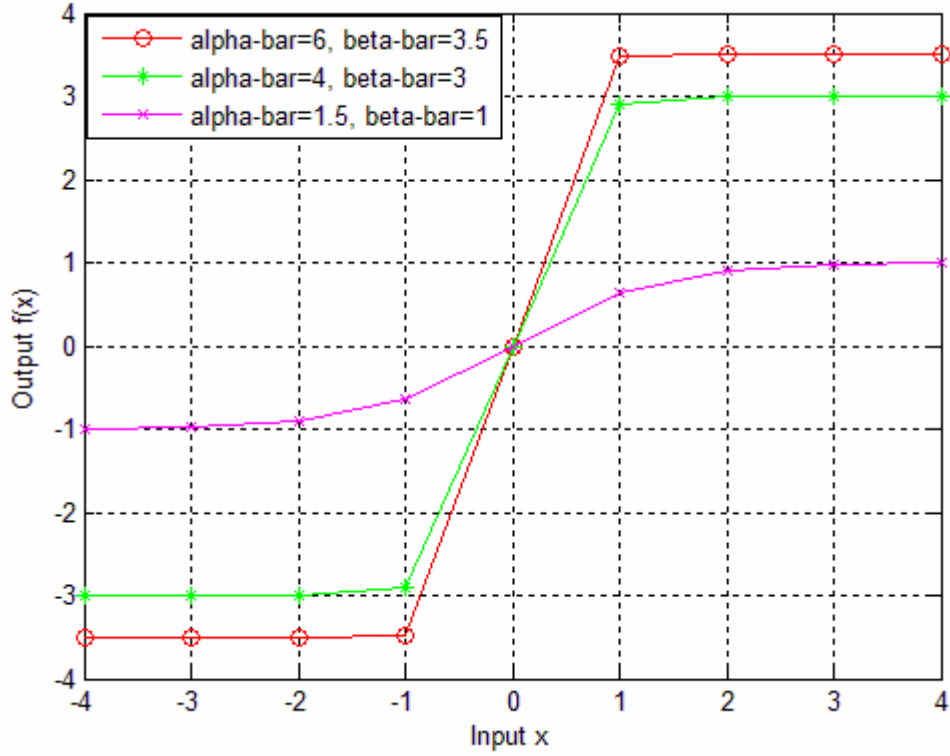


Figure 3.2.3 Nonlinear sigmoid transformation function by varying values of both  $\bar{\alpha}$  and  $\bar{\beta}$

In the Figure 3.2.1, alpha-bar represents  $\bar{\alpha}$ , which is the shape parameter of the saturation curve of loudspeaker, and this figure depicts the behaviour of sigmoid function, when we change the value of its shaping parameter and the value of clipping parameter is kept constant.

In the Figure 3.2.2, beta-bar represents  $\bar{\beta}$ , which determines the clipping value of saturation curve of the loudspeaker, and this figure depicts the behaviour of sigmoid function, when we change value of its clipping parameters, and value of shape parameter is kept constant.

From Figure 3.2.3, it can be observed that by varying the values of the sigmoid parameters  $\bar{\alpha}$  and  $\bar{\beta}$ , we can change the shape and clipping of the saturation curve of loudspeaker utilized in the acoustic systems.

From Figure 3.1, which shows a conventional acoustic echo canceller, it can be illustrated that the echo recorded by the microphone in the absence of environmental noise is

$$\tilde{d}(n) = \tilde{y}(n) \quad (3.4)$$

The output of filter that uses an adaptive algorithm based procedure is as follows

$$\hat{y}(n) = \zeta \{x(n)\} * h(n)$$

It can also be written as

$$\hat{y}(n) = \vec{h}^T(n) \zeta \{\vec{x}(n)\} \quad (3.5)$$

where,  $\vec{h}(n)$  is the impulse response coefficient vector of adaptive filter, and can be represented as

$$\vec{h}(n) = [h(0;n), h(1;n), \dots, h(M-1;n)]^T \quad (3.6)$$

$\zeta\{\vec{x}(n)\}$  can be represented as

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

Let  $u(n) = \zeta\{x(n)\}$ , which is represented as

$$\vec{u}(n) = [u(n), u(n-1), \dots, u(n-M+1)]^T \quad (3.7)$$

From Figure 3.1, the error signal may be deduced as

$$\begin{aligned} \vec{\varepsilon}(n) &= \{\tilde{y}(n) - \hat{y}(n)\} \\ &= \tilde{d}(n) - \hat{y}(n) \\ &= \tilde{d}(n) - \vec{h}^T(n)\vec{u}(n) \end{aligned} \quad (3.8)$$

Using Equation (3.6) and Equation (3.7), we obtain

$$\hat{y}(n) = \vec{h}^T(n)\vec{u}(n)$$

$$\begin{aligned} &= [h(0;n), h(1;n), \dots, h(M-1;n)] \begin{bmatrix} u(n) \\ u(n-1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ u(n-M+1) \end{bmatrix} \\ &= h(0;n)u(n) + h(1;n)u(n-1) + \dots + h(M-1;n)u(n-M+1) \\ &= \sum_{k=0}^{M-1} h(k;n)u(n-k) \end{aligned} \quad (3.9)$$

where,  $\vec{h}(n)$  is the tapped-delay-line filter coefficient vector, which can be estimated by utilizing adaptive filters. There are a number of adaptive algorithms used for updating the sigmoid feature parameters and for estimating the coefficient vector of the tapped-delay-line filter. The adaptive procedures utilized for the above purpose in this dissertation are described in the following section.

### 3.4 ALGORITHMS FOR UPDATING SIGMOID PARAMETERS

There are various adaptive algorithms, which can be utilized for updating the sigmoid parameters [17], [18], [19], [24], [25], [30] in an efficient manner, but it has been seen that the LMS algorithm is easy to handle among all adaptive algorithms. It has less complexity as well as less computational burden; and irrespective of its slow convergence, it is used in number of adaptive filter applications. To update the sigmoid parameters, various other types of LMS procedures are used in this research work, which are as follows

- a) FSS-LMS algorithm [30]
- b) RVSS-LMS algorithm [24]
- c) TMVSS-LMS algorithm [25]

These three versions of LMS algorithms are different from each other on the basis of a factor i.e., step-size. The step-size regulates (increases or decreases) the sigmoid parameter value depending upon the value of the error signal evaluated at that time.

#### 3.4.1 Fixed Step-size Least Mean Square Algorithm

In the FSS-LMS procedure [19], [20], [30], the step-size values for both the sigmoid parameters are fixed. It doesn't not change after every iteration, which means that the value of step-size for the both sigmoid parameters remains constant for each iteration. Here,  $\bar{\alpha}$  and  $\bar{\beta}$  are the two basic parameters of nonlinear sigmoid transform function, which are used to define the shape and clipping value of the nonlinear sigmoid transformation function respectively.

For FSS-LMS, the values of step-size for both sigmoid parameters ( $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$ ) i.e.,  $\mu_{\tilde{\alpha}_n}$  and  $\mu_{\tilde{\beta}_n}$  are assumed to be constant and they remains same for each iteration i.e.,

$$\mu_{\tilde{\alpha}_n}(n) = \mu_{\tilde{\beta}_n}(n) = \bar{\mu}_{FSS} = \bar{\mu}_{MIN} = 10^{-4}$$

The maximum value of step-size i.e.,  $\bar{\mu}_{FSSMAX}$  is bounded by proper limits, which are derived from simple LMS algorithm convergence situation, and can be expressed as

$$0 < \bar{\mu}_{FSSMAX} \leq \frac{2}{3tr(\bar{R})} < \frac{2}{\lambda_{MAX}}$$

where,  $\lambda_{MAX}$  is greatest eigenvalue of covariance matrix  $\bar{R} = E[\bar{x}(n)\bar{x}^T(n)]$ , when mean of  $x(n)$  is zero.

The values of step-size for both sigmoid parameters  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  are constant for all iterations.

The value of step-size for both sigmoid parameters in FSS-LMS algorithm is set as

$$\bar{\mu}_{FSS} = \bar{\mu}_{MIN}$$

This value of  $\bar{\mu}_{MIN}$  i.e., minimum value of step-size is used in RVSS and TMVSS algorithms as well.

From Equation (3.8), we may obtain mean-squared-error (MSE) as

$$\bar{J}_L(n) = E\{|\tilde{\varepsilon}(n)|^2\} \quad (3.10)$$

in Equation (3.10), the three unknown parameters are  $\tilde{\alpha}_n$ ,  $\tilde{\beta}_n$  and  $\tilde{h}(n)$ .

The FSS-LMS procedure is utilized to find optimum solution of  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$ , which is dependent on minimum-mean-square-error (MMSE) criterion, and can be represented as

$$\begin{aligned} \tilde{\alpha}_{n+1} &= \tilde{\alpha}_n(n) - \frac{\mu_{\tilde{\alpha}}}{2} \frac{\partial \bar{J}_L(n)}{\partial \tilde{\alpha}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n} \\ &= \tilde{\alpha}_n(n) + \mu_{\tilde{\alpha}} \tilde{\varepsilon}(n) \tilde{h}^T(n) \frac{\partial \bar{u}(n)}{\partial \tilde{\alpha}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n} \end{aligned} \quad (3.11)$$

Here,  $\frac{\partial \bar{u}(n)}{\partial \tilde{\alpha}}$  is a column vector, whose each element is evaluated by using Equation (3.12) as

$$\frac{\partial \zeta(x)}{\partial \tilde{\alpha}} = \frac{2x \exp(-\tilde{\alpha}x)}{[1 + \exp(-\tilde{\alpha}x)]^2} \tilde{\beta} \quad (3.12)$$

with

$$\zeta(x) = u = \frac{2\tilde{\beta}}{1 + \exp(-\tilde{\alpha}x)} - \tilde{\beta}$$

Similarly for clipping parameter  $\tilde{\beta}$ , the equations are

$$\begin{aligned} \tilde{\beta}_{n+1} &= \tilde{\beta}_n(n) - \frac{\mu_{\tilde{\beta}}}{2} \frac{\partial \bar{J}_L(n)}{\partial \tilde{\beta}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n} \\ &= \tilde{\beta}_n(n) + \mu_{\tilde{\beta}} \tilde{\varepsilon}(n) \tilde{h}^T(n) \frac{\partial \bar{u}(n)}{\partial \tilde{\beta}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n} \end{aligned} \quad (3.13)$$

Here,  $\frac{\partial \bar{u}(n)}{\partial \tilde{\beta}}$  is a column vector, whose each element is evaluated by using Equation (3.14) as

$$\frac{\partial \zeta(x)}{\partial \tilde{\beta}} = \frac{2}{1 + \exp(-\tilde{\alpha}x)} - 1 \quad (3.14)$$

The convergence rate of FSS-LMS algorithm is very low, and the MSE value is high. In order to increase the convergence rate, VSS-LMS algorithm and its versions can be utilized for updating the parameters of sigmoid nonlinear transformation function.

### 3.4.2 Robust Variable Step-size Least Mean Square Algorithm [24]

The majority of applications utilize LMS procedure with a constant step-size. There is a tradeoff between misadjustment and rate of adaptation for the choice of step-size. From usage of FSS-LMS procedure in various applications, it has been seen that a fixed step-size algorithm does not track changes in the system effectively. Subsequent research work details the issue of optimization of step-size or the schemes for changing the step-size to enhance performance [24]. In [24], an idea of a variable step-size procedure, that is easy to incorporate and is capable of providing fast tracking as well as small misadjustment, is presented by Kwong and Johnston.

In the RVSS-LMS procedure, the values of step-sizes for both  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  i.e.,  $\mu_{\tilde{\alpha}_n}(n)$  and  $\mu_{\tilde{\beta}_n}(n)$  are made variable i.e., these vary after every iteration (either increase or decrease) depending upon the value of error signal i.e.,  $\tilde{\varepsilon}(n)$  at that instant. However, the maximum and minimum values of both  $\mu_{\tilde{\alpha}}$  and  $\mu_{\tilde{\beta}}$  are fixed, so that both of them are bounded by proper limits, which are obtained according to conditions given in [24].

The RVSS-LMS procedure is utilized to find the optimum solution of  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$ , and the parameters update equations are as follows

$$\begin{aligned}\tilde{\alpha}_{n+1} &= \tilde{\alpha}_n(n) - \frac{\mu_{\tilde{\alpha}}(n)}{2} \frac{\partial \bar{J}_L(n)}{\partial \tilde{\alpha}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n} \\ &= \tilde{\alpha}_n(n) + \mu_{\tilde{\alpha}}(n) \tilde{\varepsilon}(n) \vec{h}^T(n) \frac{\partial \vec{u}(n)}{\partial \tilde{\alpha}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n}\end{aligned}\quad (3.15)$$

Here,  $\frac{\partial \vec{u}(n)}{\partial \tilde{\alpha}}$  is column vector, whose each element is evaluated by using Equation (3.16) as

$$\frac{\partial \zeta(x)}{\partial \tilde{\alpha}} = \frac{2x \exp(-\tilde{\alpha}x)}{[1 + \exp(-\tilde{\alpha}x)]^2} \tilde{\beta} \quad (3.16)$$

with

$$\zeta(x) = u = \frac{2\tilde{\beta}}{1 + \exp(-\tilde{\alpha}x)} - \tilde{\beta}$$

Similarly for clipping parameter  $\tilde{\beta}$ , the parameter update equations are as

$$\begin{aligned}\tilde{\beta}_{n+1} &= \tilde{\beta}_n(n) - \frac{\mu_{\tilde{\beta}}(n)}{2} \frac{\partial \bar{J}_L(n)}{\partial \tilde{\beta}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n} \\ &= \tilde{\beta}_n(n) + \mu_{\tilde{\beta}}(n) \tilde{\varepsilon}(n) \vec{h}^T(n) \frac{\partial \vec{u}(n)}{\partial \tilde{\beta}} \Big|_{\tilde{\alpha}=\tilde{\alpha}_n; \tilde{\beta}=\tilde{\beta}_n}\end{aligned}\quad (3.17)$$

Here,  $\frac{\partial \vec{u}(n)}{\partial \tilde{\beta}}$  is column vector, whose each element is evaluated by using Equation (3.18)

$$\frac{\partial \zeta(x)}{\partial \tilde{\beta}} = \frac{2}{1 + \exp(-\tilde{\alpha}x)} - 1 \quad (3.18)$$

For RVSS-LMS procedure, the values of  $\mu_{\tilde{\alpha}_n}(n)$  and  $\mu_{\tilde{\beta}_n}(n)$ , which are updated after every iteration, are derived from the following equations

$$\bar{\mu}_{RVSS}(n+1) = \left\{ \begin{array}{ll} \bar{\mu}_{RVSSMAX} & \text{if } \bar{\mu}_{RVSS}(n) > \bar{\mu}_{RVSSMAX} \\ \bar{\mu}_{RVSSMIN} & \text{if } \bar{\mu}_{RVSS}(n) < \bar{\mu}_{RVSSMIN} \\ \bar{\mu}_{RVSS}(n) & \text{otherwise} \end{array} \right\} \quad (3.19)$$

$$\bar{\mu}_{RVSS}(n+1) = \bar{\alpha}_{RVSS} \bar{\mu}_{RVSS}(n) + \bar{\gamma}_{RVSS} \tilde{\epsilon}_{RVSS}^2 \quad (3.20)$$

where,  $0 < \bar{\alpha}_{RVSS} < 1$  and  $1 > \bar{\gamma}_{RVSS} > 0$  are adjusted to have minimum possible misadjustment. The  $\bar{\alpha}_{RVSS}$  and  $\bar{\gamma}_{RVSS}$  are the parameters of RVSS-LMS procedure. The initial step-size is usually set at  $\bar{\mu}_{RVSSMAX}$ , although this procedure is not solely dependent on choice. The step-size is always positive and is tuned by size of prediction error, parameters  $\bar{\alpha}_{RVSS}$  and  $\bar{\gamma}_{RVSS}$ . Intuitively speaking, a large prediction error boosts step-size to give faster tracking. If prediction error alleviates, the step-size gets alleviated to decrease misadjustment. The choice of the constant  $\bar{\mu}_{RVSSMAX}$  is made to assure, that MSE of this procedure remains bounded. A sufficient condition for this is same as for FSS-LMS procedure. For RVSS-LMS algorithm, the values of  $\bar{\mu}_{RVSSMAX}$  and  $\bar{\mu}_{RVSSMIN}$  for both  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  are set according to Equation (3.19), and given as

$$\bar{\mu}_{RVSSMIN} = \bar{\mu}_{FSS} = \bar{\mu}_{MIN} \quad \text{and} \quad 0 < \bar{\mu}_{RVSSMAX} \leq \frac{2}{3tr(\bar{R})}, \quad \text{where } \bar{R} = E[\bar{x}(n)\bar{x}^T(n)] \text{ is covariance}$$

matrix, when mean of  $x(n)$  is zero.

### 3.4.3 Modified Variable Step-size Least Mean Square Algorithm [25]

It has been seen that FSS-LMS and RVSS-LMS procedures work efficiently for updating the sigmoid parameter values. But, the experimentation of these procedures indicate that their performance is highly sensitive to noise disturbances. The TMVSS-LMS type procedure yields fast convergence at early stages of adaptation, while assuring low final misadjustment. Moreover, characteristics of this procedure is not affected by existing uncorrelated noise disturbances.

In the TMVSS-LMS, the values of step-size of both  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  i.e.,  $\mu_{\tilde{\alpha}_n}(n)$  and  $\mu_{\tilde{\beta}_n}(n)$  are made variable i.e., these vary after every iteration (either increases or decreases)

depending upon the value of MSE at each iteration. However, in TMVSS-LMS algorithm [25], the step-size of procedure is tuned in accordance with square of time-averaged estimate of the autocorrelation of  $\tilde{\varepsilon}(n)$  and  $\tilde{\varepsilon}(n-1)$  i.e., error signals. In this case, maximum and minimum values of both  $\mu_{\tilde{\alpha}_n}$  and  $\mu_{\tilde{\beta}_n}$  are also fixed, so that both of these are bounded in limits, which are according to conditions provided in [25]. To find the optimal solution for  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$ , same equations are used as in RVSS-LMS algorithm. But, in this case, values of  $\mu_{\tilde{\alpha}_n}(n)$  and  $\mu_{\tilde{\beta}_n}(n)$ , which are updated after every iteration, are derived from the conditions given in following equations

$$\bar{\mu}_{TMVSS}(n+1) = \left\{ \begin{array}{ll} \bar{\mu}_{TMVSSMAX} & \text{if } \bar{\mu}_{TMVSS}(n) > \bar{\mu}_{TMVSSMAX} \\ \bar{\mu}_{TMVSSMIN} & \text{if } \bar{\mu}_{TMVSS}(n) < \bar{\mu}_{TMVSSMIN} \\ \bar{\alpha}_{TMVSS} \bar{\mu}_{TMVSS}(n) + \bar{\gamma}_{TMVSS} \tilde{q}_{TMVSS}^2(n) & \text{otherwise} \end{array} \right\} \quad (3.21)$$

$$\tilde{q}_{TMVSS}(n+1) = \bar{\beta}_{TMVSS} \tilde{q}_{TMVSS}(n) + (1 - \bar{\beta}_{TMVSS}) \tilde{\varepsilon}_{TMVSS}(n+1) \tilde{\varepsilon}_{TMVSS}(n) \quad (3.22)$$

where,  $0 < \bar{\alpha}_{TMVSS} < 1$ ,  $1 > \bar{\gamma}_{TMVSS} > 0$  and  $0 < \bar{\beta}_{TMVSS} < 1$  are adjusted to have minimum possible misadjustment. The constant  $\bar{\mu}_{TMVSSMAX}$  is normally selected high as compared to the FSS-LMS, in order to achieve maximum possible convergence speed. The condition to update values of  $\mu_{\tilde{\alpha}_n}(n)$  and  $\mu_{\tilde{\beta}_n}(n)$  in TMVSS-LMS is somewhat different from RVSS-LMS. In case of TMVSS-LMS, the autocorrelation among the subsequent error signal samples is used as reference, but this is not evaluated in case of RVSS-LMS algorithm. The conditions for  $\bar{\mu}_{TMVSSMAX}$  and  $\bar{\mu}_{TMVSSMIN}$  are same as in RVSS-LMS procedure. The  $\bar{\alpha}_{TMVSS}$ ,  $\bar{\gamma}_{TMVSS}$  and  $\bar{\beta}_{TMVSS}$  are the parameters of TMVSS-LMS procedure. For TMVSS-LMS algorithm, the values of  $\bar{\mu}_{TMVSSMAX}$  and  $\bar{\mu}_{TMVSSMIN}$  for both  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$ , are set according to Equation (3.21) and Equation (3.22), such that

$$\bar{\mu}_{TMVSSMIN} = \bar{\mu}_{FSS} = \bar{\mu}_{MIN} \quad \text{and} \quad 0 < \bar{\mu}_{TMVSSMAX} \leq \frac{2}{3tr(\bar{R})}, \quad \text{where } \bar{R} = E[\bar{x}(n)\bar{x}^T(n)] \text{ is covariance}$$

matrix, when mean of  $x(n)$  is zero.

### 3.5 ALGORITHMS FOR ESTIMATING THE COEFFICIENT VECTOR OF TAPPED-DELAY-LINE FILTER

There are various adaptive algorithms, which can be used for the estimation of coefficient vector of the tapped-delay-line finite-impulse-response (FIR) filter. To estimate the

coefficient vector of tapped-delay-line filter, the adaptive algorithms used in this research work are

- a) NLMS algorithm (normalized-least-mean-square)
- b) RLS algorithm (recursive-least-square)

### 3.5.1 Normalized Least Mean Square Algorithm

In the NLMS algorithm [19], [30], [31], to estimate the values of the coefficient vector of the FIR filter  $\vec{h}(n)$ , the following equation is used

As  $\vec{u}(n) = \zeta(\vec{x}(n))$

$$\vec{h}(n+1) = \vec{h}(n) + \bar{\mu}_N \frac{\tilde{\varepsilon}(n)\vec{u}(n)}{\bar{c}_N + \vec{u}^T(n)\vec{u}(n)} \quad (3.23)$$

where,  $\bar{\mu}_N$  is the step-size and  $\tilde{\varepsilon}(n)$  represents the error signal, which is real in nature and  $u(n)$  denotes the real input signal. If input signal is complex in nature, in the place of transpose of signal, Hermitian of signal is considered. The  $\bar{\mu}_N$  is fixed in NLMS procedure [19], [30]. The regularization factor  $\bar{c}_N$  is a constant, whose value is small and is used for proper working of the NLMS algorithm. It is used so that the denominator of NLMS algorithm doesn't become '0', otherwise the NLMS algorithm fails.

### 3.5.2 Recursive Least Square Algorithm

In this case, we adopt the RLS procedure without considering the effect of noise in its performance characteristics. This algorithm estimates and updates the weight vector  $\vec{h}(n)$  of the tapped-delay-line filter effectively, because of its fast convergence rate [19], [20], [29], [30]. The RLS procedure may be briefly detailed as follows

The cost function for RLS procedure can be represented as

$$\bar{J}_R(n) = \sum_{i=M}^n [\bar{\lambda}_R(n)]^{n-i} |\tilde{\varepsilon}(i)|^2 \quad (3.24)$$

$\bar{e}(n) = \tilde{d}(n) - \vec{h}^T(n-1)\vec{u}(n)$ , which is *a priori* estimation error signal.

where,

$$\vec{u}(n) = \zeta\{\vec{x}(n)\}$$

Let

$$\vec{\theta}_R(n) = \bar{P}_R(n-1)\vec{u}(n)$$

$$\begin{aligned}\bar{K}_R(n) &= \frac{\bar{P}_R(n-1)\bar{u}(n)}{\bar{\lambda}_R(n) + \bar{u}^T(n)\bar{P}_R(n-1)\bar{u}(n)} \\ &= \frac{\bar{\theta}_R(n)}{\bar{\lambda}_R(n) + \bar{u}^T(n)\bar{\theta}_R(n)}\end{aligned}\quad (3.25)$$

$$\bar{P}_R(n) = \frac{1}{\bar{\lambda}_R(n)} \left[ \bar{P}_R(n-1) - \bar{K}_R(n)\bar{u}^T(n)\bar{P}_R(n-1) \right] \quad (3.26)$$

$$\bar{h}(n) = \bar{h}(n-1) + \bar{K}_R(n)\bar{e}(n) \quad (3.27)$$

where,  $\bar{\lambda}_R$  is a small positive constant (forgetting factor) very near to 1, but smaller than 1,  $\delta$  is the regularizing parameter for RLS algorithm.

*A posteriori* estimate of  $\bar{c}(n)$  is evaluated by using

$$\bar{h}(0) = \text{null vector}$$

$$\bar{P}_R(0) = \delta^{-1}I$$

Since our knowledge of such parameters at  $n=0$  is too vague, we must assign a high value to  $\delta$ . For large data length, the initial values assigned at  $n=0$  are not important, since these are forgotten because of exponential forgetting factor  $\bar{\lambda}_R$ , and  $\bar{u}(n)$  is the input signal to the tapped-delay-line filter, which is real in nature.

In this research work, different inputs are given to the presented NAEC. Four different input cases are taken into account independently, and MSE is calculated separately for each case and compared with each other. The inputs used are the Gaussian input signaling waveform [37], the AR(1) input signaling waveform with  $\bar{\rho}_{c_0} = 0.1$  [38], [39], the AR(1) input signaling waveform with  $\bar{\rho}_{c_0} = 0.9$  [38], [39]; where  $\bar{\rho}_{c_0}$  represents the correlation coefficient and the AR(2) input signaling waveform [30], [40], [41] for all simulations. These inputs are different from each other depending upon the relationship that exists between the present and past samples values of these signals. The relation between the past and present sample values of input signal depend upon the value of the correlation coefficient i.e., the value of  $\bar{\rho}_{c_0}$ . If its value is high, it means correlation is strong; while if its value is low, then correlation is weak between the samples of input signal. The Gaussian input signal is uncorrelated in nature, which means that the sample values are independent from each other and are random in nature. Among all these four input signals, the AR(2) input signal exhibits highest correlation among its samples. This is because in the AR(2) input signal, the value of present sample depends upon the previous two sample values, however in case of the AR(1) input signal, this is depends upon only one past sample value.

### 3.6 ECHO RETURN LOSS ENHANCEMENT AND MEAN SQUARED ERROR

To evaluate and compare the performance of the NAEC, the echo-return-loss-enhancement (ERLE) and mean-squared-error (MSE) are calculated for different types of inputs independently.

The ERLE is calculated using the formula given as below

$$ERLE(n)(dB) = 10 \log_{10} \frac{E |\tilde{d}(n)|^2}{E |\tilde{\varepsilon}(n)|^2}$$

which is ensemble-average.

$$ERLE(n)(dB) \approx 10 \log_{10} \left[ \frac{\sum_{j=1}^{250} \{|\tilde{d}(n; j)|^2 / 250\}}{\sum_{j=1}^{250} \{|\tilde{\varepsilon}(n; j)|^2 / 250\}} \right] \quad (3.28)$$

which is time-average and MSE is calculated as

$$MSE(n) = E[(\tilde{y}(n) - \tilde{h}^T(n) \zeta \{ \bar{x}(n) \})^2]$$

which is ensemble-average.

$$MSE(n) \approx \sum_{j=1}^{250} \left\{ \left| \tilde{d}(n; j) - \hat{y}(n; j) \right|^2 \right\} / 250 \quad (3.29)$$

which is time-average.

### 3.7 SIMULATION RESULTS

We shall investigate the behaviour of NAEC in the convergence and tracking modes, using different types of adaptive algorithms. Adaptive algorithms are used for updating parameters of nonlinear sigmoid transformation function and to estimate coefficient vector of tapped-delay-line FIR filter. For simulation, the number of samples in input signal vector is  $M=64$ , the length of  $\bar{c}(n)$  is kept  $M$ , which is the impulse response coefficient vector of room (indoor) i.e., multipath in nature.

These coefficients are considered to be static and may be represented as

$$c(k) = \begin{cases} \frac{1}{M}, & 0 \leq k \leq M-1 \\ zero, & otherwise \end{cases} \quad (3.30)$$

The echo generated by the loudspeaker is expressed as

$$\tilde{y}(n) = f \{ x(n) \} * c(n) \quad (3.31)$$

where,  $*$  represents the linear convolution operation, and Equation (3.31) can also be expressed by

$$\tilde{y}(n) = \bar{c}^T(n) f \{ \bar{x}(n) \} \quad (3.32)$$

where,  $f\{\bar{x}(n)\}$  indicates the nonlinear response of loudspeaker (akin to sigmoid function), and it is same as Equation (3.2).

First, the evaluation of ERLE of conventional NAEC by using two different inputs viz. the Gaussian signal (which is uncorrelated in nature) and correlated signal is performed. Then, the evaluation of MSE and ERLE of NAEC is performed by using different input signals given to NAEC. The input signals are Gaussian signal [37], AR(1) signal with  $\bar{\rho}_{c0} = 0.1$  [38], [39], AR(1) signal with  $\bar{\rho}_{c0} = 0.9$  [38], [39] and AR(2) signal [30], [40], [41]. All simulation trials are performed using MATLAB. We shall compare the performance of FSS-LMS [30], RVSS-LMS [24] and TMVSS-LMS [25] procedures utilized for updating sigmoid parameters, and in addition to this, we shall also compare the performance of RLS and/or NLMS algorithms used to estimate the coefficient vector of tapped-delay-line filter. The presented outcomes are based on ensemble average of 250 independent simulation trials using various types of inputs given to NAEC. In these simulation trials, only single talk case is considered.

In cases mentioned below, the ERLE comparison of the conventional nonlinear acoustic echo canceller is performed using different adaptive algorithms. The ERLE is evaluated using the Equation (3.28). In this section, ERLE of the conventional NAEC is evaluated, and simulation outcomes are established for ERLE by the usage of only FSS-LMS procedure for updating the parameters of sigmoid characteristic. For estimating the coefficient vector of tapped-delay-line filter, the RLS or the NLMS algorithms are utilized, so that we can choose best out of these two adaptive procedures for estimating the tapped-delay-line filter coefficient vector. In case of uncorrelated and correlated input signals, following combination of adaptive algorithms are utilized

- a) FSS-LMS and RLS algorithm
- b) FSS-LMS and NLMS algorithm

In FSS-LMS and RLS algorithm based NAEC, the former algorithm is used for updating the parameters of sigmoid-type nonlinearity and latter algorithm is used for estimating the coefficient vector of the tapped-delay-line FIR filter. Similarly, in FSS-LMS and NLMS algorithm based NAEC, FSS-LMS algorithm is used for updating parameters of sigmoid-type nonlinearity and NLMS procedure is used for estimating the coefficient vector of tapped-delay-line FIR filter.

The assessment of NLMS and RLS algorithm is completed in both input cases one by one. The values of sigmoid parameters in Equation (3.2) i.e.,  $\bar{\alpha}$  and  $\bar{\beta}$  for actual loudspeaker model case are set equal to 4 and 3 respectively, and then these are estimated using adaptive procedures. For the Figure 3.7.1 and Figure 3.7.2 the value of parameters of FSS-LMS adaptive procedure and the value of parameters of RLS and/or NLMS procedure are set as given below

For FSS-LMS procedure, the values of step-size for both sigmoid parameters are set as

$$\mu_{\bar{\alpha}_n}(n) = \mu_{\bar{\beta}_n}(n) = \bar{\mu}_{FSS} = \bar{\mu}_{MIN} = 10^{-4},$$

and it remains unchanged for each iteration. The value of forgetting factor  $\bar{\lambda}_R$  in RLS procedure used for the estimation of coefficient vector of tapped-delay-line filter is constant at 0.97, and the value of regularizing parameter  $\delta^{-1}$  is set at 0.005 for each input case. The value of small regularization factor  $\bar{c}_N$  for NLMS procedure is kept at 0.0019 for each input case.

#### Case 3.7.1:- ERLE Comparison of Conventional NAEC Using Gaussian Input Signal

In this first case, Gaussian signal [37] is given as input signal to the conventional NAEC, which is uncorrelated in nature, which in turn implies that past and previous sample values of input signal do not depend upon each other. All parameters related to sigmoid-type nonlinearity and corresponding to the algorithm used for the tapped-delay-line filter coefficient vector estimation are set as mentioned above. As Gaussian signal is given as input to the conventional NAEC, so it is the most general and basic case because the Gaussian signal is considered as a basic signal. The ERLE data in the graph is plotted on dB scale.

In this case, Gaussian signal is given as input signal to the presented NAEC having mean  $m_x = 0$  and variance  $\sigma_x^2 = 1$ .

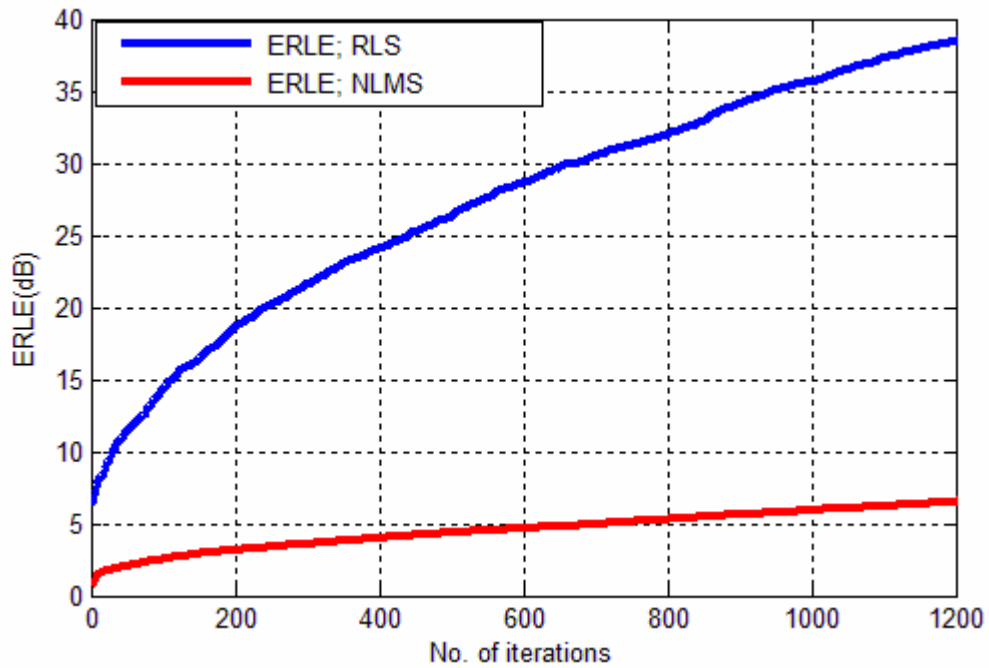


Figure 3.7.1 ERLE comparison of NAEC using Gaussian input signal

In the above figure, RLS and NLMS depict that, which adaptive algorithm is used for the estimation of coefficient vector of the tapped-delay-line filter.

The ERLE outcomes in Figure 3.7.1 manifest that ERLE is high in the case of combination of FSS-LMS and RLS algorithm based NAEC as compared to the combination of FSS-LMS and NLMS algorithm based NAEC, when the Gaussian signal is given as input signal. This is due to the high convergence rate of RLS procedure as compared to NLMS procedure. The RLS algorithm also exhibits low level of misadjustment as compared to the NLMS algorithm. The values of ERLE for different combination of algorithms using Gaussian signal as input signal at iteration number 1200 are

S.No	Type of NAEC	ERLE Value (dB) (Approx.)
1.	FSS-LMS and NLMS algorithm based NAEC	7 dB
2.	FSS-LMS and RLS algorithm based NAEC	38 dB

Table 3.1 ERLE Comparison for Different Types of NAEC Using Gaussian Input Signal

From the Table 3.1, it is clear that RLS algorithm based NAEC outperforms the NLMS algorithm based NAEC in terms of ERLE factor evaluation, when Gaussian signal is given as input to the conventional NAEC. In terms of ERLE, there is a benefit of approximately 31 dB, if we use the FSS-LMS and RLS algorithm based NAEC as compared to the FSS-LMS and NLMS algorithm based NAEC. This is due to low misadjustment level of RLS algorithm as compared to NLMS adaptive algorithm.

#### Case 3.7.2:- ERLE Comparison of Conventional NAEC Using Correlated Input Signal

In this case, the correlated signal [38], [39] is given as input signal to the conventional NAEC. As the input to conventional NAEC is a correlated signal, it means that previous and present input samples are correlated with each other, and therefore, future sample values of the input can be predicted by analyzing the specific number of previous input sample values. The ERLE data in the graph is plotted on dB scale.

In this case, the correlated signal is given as input signal to the presented NAEC, and it is obtained by using the equation,

$$x(n) = \bar{\rho}_{c0}x(n-1) + \bar{v}(n)$$

where,  $\bar{\rho}_{c0}$  denotes the AR(1) coefficient or correlation coefficient, and the value of this correlation coefficient decides the correlation present between the samples of the AR(1) input signal. In AR(1) signal, the value of the next input sample depends upon the preceding input sample value. The mean and variance of white Gaussian noise  $\bar{v}(n)$  is set equal to zero and  $\sigma_v^2 = \sigma_x^2(1 - \bar{\rho}_{c0}^2)$  respectively, which leads to the generation of input signal  $x(n)$  with zero-mean and unity variance.

The value of variance  $\sigma_v^2$  is equal to 0.75, when  $\bar{\rho}_{c0} = 0.5$ .

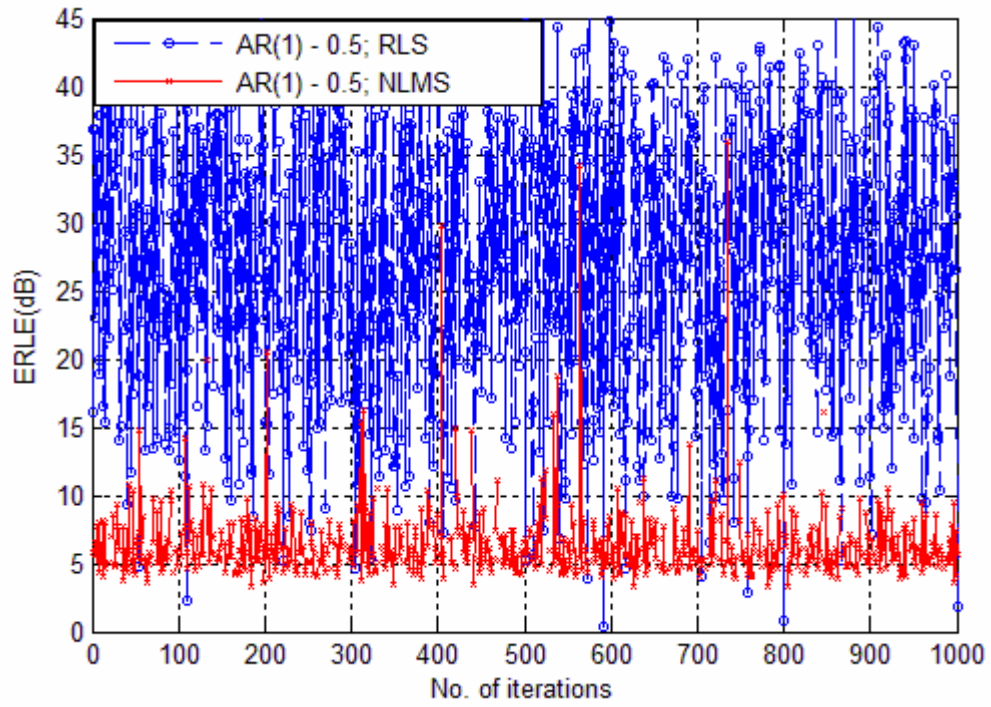


Figure 3.7.2 ERLE comparison of conventional NAEC using correlated input signal (single trial)

In the above figure, AR(1)-0.5 denotes that AR(1) signal (which is a correlated signal) is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c_0} = 0.5$ .

The ERLE outcomes in Figure 3.7.2 reveal that ERLE is high in case of the combination of FSS-LMS and RLS algorithm based NAEC as compared to the combination of FSS-LMS and NLMS algorithm based NAEC, when correlated signal is given as input signal. This is due to high convergence rate of RLS procedure as compared to the NLMS procedure as well as because of small mean squared error of RLS procedure as compared to NLMS procedure. The values of ERLE for different combinations of algorithms using correlated input signal at 1000<sup>th</sup> iteration are

S.No	Type of NAEC	ERLE Value (dB) (Approx.)
1.	FSS-LMS and NLMS based NAEC	10 dB
2.	FSS-LMS and RLS based NAEC	45 dB

Table 3.2 ERLE Comparison for Different Types of NAEC Using Correlated Input Signal (Random Check in Single Trial)

As from the Table 3.2, it is clear that RLS algorithm based NAEC outperforms the NLMS algorithm based NAEC in terms of ERLE factor evaluation, when correlated signal is given as input to the conventional NAEC. In terms of ERLE, there is a benefit of approximately 35 dB (random check as shown in Figure 3.7.2) if we utilize FSS-LMS and RLS algorithm based NAEC to estimate the coefficient vector of the tapped-delay-line filter instead of FSS-LMS and NLMS algorithm based NAEC. This is due to its low misadjustment level, when correlated signal is given as input to the NAEC using RLS algorithm.

From the Table 3.1 and Table 3.2, it is apparent that FSS-LMS and RLS algorithm based NAEC outperforms the FSS-LMS and NLMS algorithm based NAEC, in terms of ERLE factor evaluation whether we give Gaussian signal as input signal or correlated signal as input signal to the presented NAEC.

### **3.8 MSE PERFORMANCE OF VSS-LMS AND RLS ALGORITHM BASED NAEC UNDER IDEAL CONDITIONS**

In this section, we shall investigate the behaviour of presented nonlinear acoustic echo canceller using different types of VSS-LMS adaptive algorithms. The adaptive algorithms are used for updating parameters of nonlinear sigmoid transformation function and to estimate coefficient vector of the tapped-delay-line filter in absence of environmental noise. For simulation, the number of samples in input signal vector is  $M=64$ , the length of  $\vec{c}(n)$ , which is the impulse response coefficient vector of room (indoor) i.e., multipath in nature, is also  $M=64$ . These coefficients are considered to be static and are set according to Equation (3.30).

The MSE evaluation of NAEC is conducted by using different input signals given to NAEC viz. Gaussian signal [37], AR(1) signal with  $\bar{\rho}_{c_0} = 0.1$  [38], [39], AR(1) signal with  $\bar{\rho}_{c_0} = 0.9$  [38], [39] and AR(2) signal [30], [40], [41] in the absence of environmental noise. All simulation trials are carried out using MATLAB. We shall compare the performance of FSS-LMS, RVSS-LMS and TMVSS-LMS procedures used for updating sigmoid parameters. From the above simulated results (in previous section), it is apparent that whether the input signal is Gaussian in nature or Correlated in nature, the FSS-LMS and RLS algorithm based NAEC outperforms the FSS-LMS and NLMS algorithm based NAEC for all the input signal cases. Further, we discuss the results using only RLS procedure to estimate the coefficient vector of the tapped-delay-line FIR filter in the absence of environmental. In this section, we evaluate and compare performance of different VSS-LMS procedures utilized for updating parameters of nonlinear sigmoid transformation function. The presented outcomes are

dependent on ensemble average of 250 independent simulation trials using various types of input signals fed to the presented NAEC.

In case of all four different input signals, the MSE performance of nonlinear acoustic echo canceller is evaluated in the absence of environmental noise. The MSE is calculated using the Equation (3.29). Simulation outcomes are established for MSE by the usage of FSS-LMS [30], RVSS-LMS [24] and TMVSS-LMS [25] algorithms for updating the parameters of sigmoid characteristic.

For estimating the coefficient vector of the tapped-delay-line FIR filter the RLS algorithm [19], [29], [30], [32] is employed in the absence of any noise component.

The assessment of FSS-LMS, RVSS-LMS and TMVSS-LMS is accomplished for each input case one by one. The values of sigmoid parameters i.e.,  $\bar{\alpha}$  and  $\bar{\beta}$  in Equation (3.2) i.e., for actual loudspeaker nonlinearity case are set equal to 4 and 3 respectively, and then tracked by utilizing VSS-LMS adaptive algorithms. The value of forgetting coefficient  $\bar{\lambda}_R$  for RLS procedure is kept 0.97, and the value of regularizing parameter  $\delta^{-1}$  is kept 0.005 in each input case. For the Figures 3.8.1 – 3.8.4, the value of parameters used for updating the sigmoid parameters are set as given below

For FSS-LMS algorithm, the value of step-sizes for both sigmoid parameters are set as

$$\mu_{\tilde{\alpha}_n}(n) = \mu_{\tilde{\beta}_n}(n) = \bar{\mu}_{FSS} = \bar{\mu}_{MIN} = 10^{-4},$$

and it remains constant for every iteration. For RVSS-LMS algorithm, the values of  $\bar{\mu}_{RVSSMAX}$  and  $\bar{\mu}_{RVSSMIN}$  for both  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  are set according to Equation (3.19), and which are given as

$$\bar{\mu}_{RVSSMIN} = \bar{\mu}_{FSS} = \bar{\mu}_{MIN} \quad \text{and} \quad \bar{\mu}_{RVSSMAX} = \frac{2}{3tr(\bar{R})}. \quad \text{The value of } \bar{\alpha}_{RVSS} \text{ is kept 0.97 and } \bar{\gamma}_{RVSS} \text{ is set}$$

at  $8 \times 10^{-4}$  in RVSS-LMS procedure. The values of  $\mu_{\tilde{\alpha}_n}(n)$  and  $\mu_{\tilde{\beta}_n}(n)$  are updated according to the Equation (3.20).

For TMVSS-LMS algorithm, the values of  $\bar{\mu}_{TMVSSMAX}$  and  $\bar{\mu}_{TMVSSMIN}$  for both  $\tilde{\alpha}_n$  and  $\tilde{\beta}_n$  are set according to Equation (3.21) and Equation (3.22), which are given as

$$\bar{\mu}_{TMVSSMIN} = \bar{\mu}_{FSS} = \bar{\mu}_{MIN} \quad \text{and} \quad \bar{\mu}_{TMVSSMAX} = \frac{2}{3tr(\bar{R})}. \quad \text{The value of } \bar{\alpha}_{TMVSS} \text{ is kept 0.97, and } \bar{\gamma}_{TMVSS}$$

is set equal to  $8 \times 10^{-4}$ , and  $\bar{\beta}_{TMVSS}$  is set equal to 0.97 in the TMVSS-LMS procedure. The initial value of  $\tilde{q}(n)$  at the starting point of algorithm is set equal to zero (as in [25]).

### Case 3.8.1:- MSE Performance of NAEC Using Gaussian Input Signal

In this case, the mean squared error performance of nonlinear acoustic echo canceller is evaluated in the absence of environmental noise. The MSE is evaluated using the Equation (3.29). In this case, Gaussian signal [37]  $x(n)$  is given as input signal to the NAEC having mean  $m_x = 0$  and variance  $\sigma_x^2 = 1$ . The MSE data in the graph is plotted on the semilog scale.

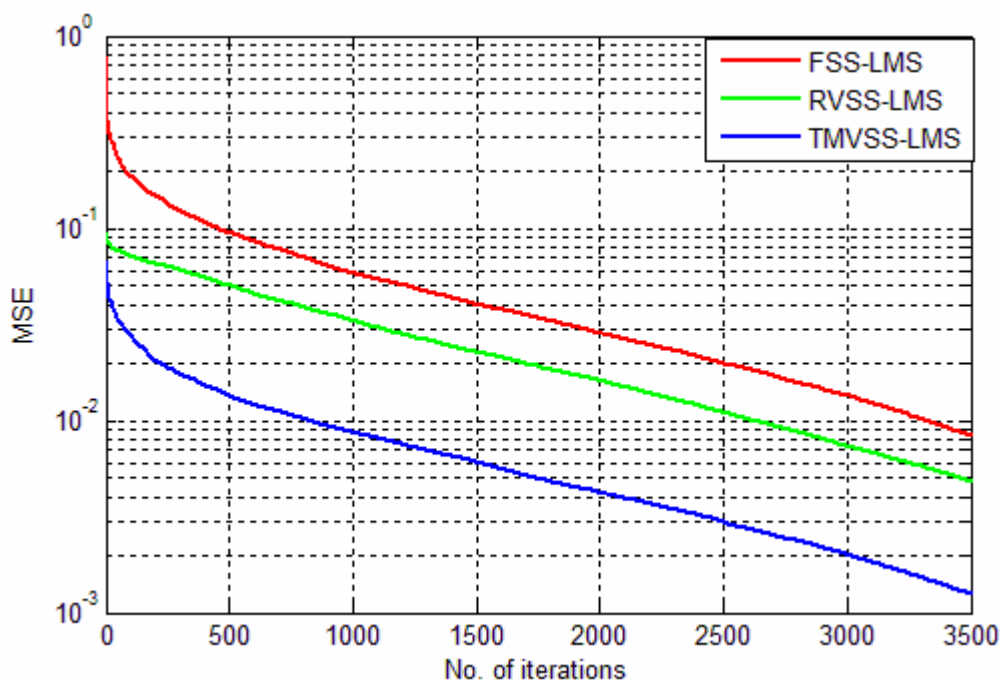


Figure 3.8.1 MSE performance of NAEC using Gaussian input signal

Figure 3.8.1 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS algorithms for Gaussian input case, which are used for updating sigmoid parameter values.

At 500<sup>th</sup> iteration, for the Gaussian input signal, it is observed from results presented in Figure 3.8.1 that the TMVSS-LMS and RLS algorithm based NAEC performs approximately 5.7 dB better than RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance advantage of former case increases to approximately 8.45 dB in comparison to FSS-LMS and RLS algorithm based NAEC.

The MSE results in Figure 3.8.1 manifest that for Gaussian input signal, the overall MSE is high in case of the FSS-LMS and RLS algorithm based NAEC and least in case of the TMVSS-LMS and RLS algorithm based NAEC. It is due to the step-size parameter, which remains constant in the FSS-LMS algorithm, used for sigmoid parameters updation. All the three adaptive algorithms used for updating sigmoid parameters converge at different rates as inferred from the Figure 3.8.1. It is clear from the Figure 3.8.1 that TMVSS-LMS algorithm converges in approximately 500 iterations, while other two algorithms take more number of iterations for convergence to the same point.

Case 3.8.2:- MSE Performance of NAEC Using AR(1) Input Signaling Waveform with Correlation Coefficient Equal to 0.1

In this case, MSE performance of the NAEC is evaluated using the Equation (3.29). The MSE data in the graph is plotted on the semilog scale.

In this case, AR(1) signal [38], [39] with correlation coefficient  $\bar{\rho}_{c0} = 0.1$  is given as input to the presented NAEC. The AR(1) signal is obtained by utilizing the equation, which is expressed as

$$x(n) = \bar{\rho}_{c0}x(n-1) + \bar{v}(n) ,$$

where,  $\bar{\rho}_{c0}$  denotes the AR(1) coefficient or correlation coefficient, and the value of this coefficient decides the correlation between two successive input sample values. To make variance of input signal  $\sigma_x^2 = 1$ , the parameters of white Gaussian noise  $\bar{v}(n)$  are set as mean  $m_{\bar{v}} = 0$  , and variance  $\sigma_{\bar{v}}^2 = \sigma_x^2(1 - \bar{\rho}_{c0}^2)$ .

The value of variance  $\sigma_{\bar{v}}^2$  is equal to 0.99, when  $\bar{\rho}_{c0} = 0.1$ .

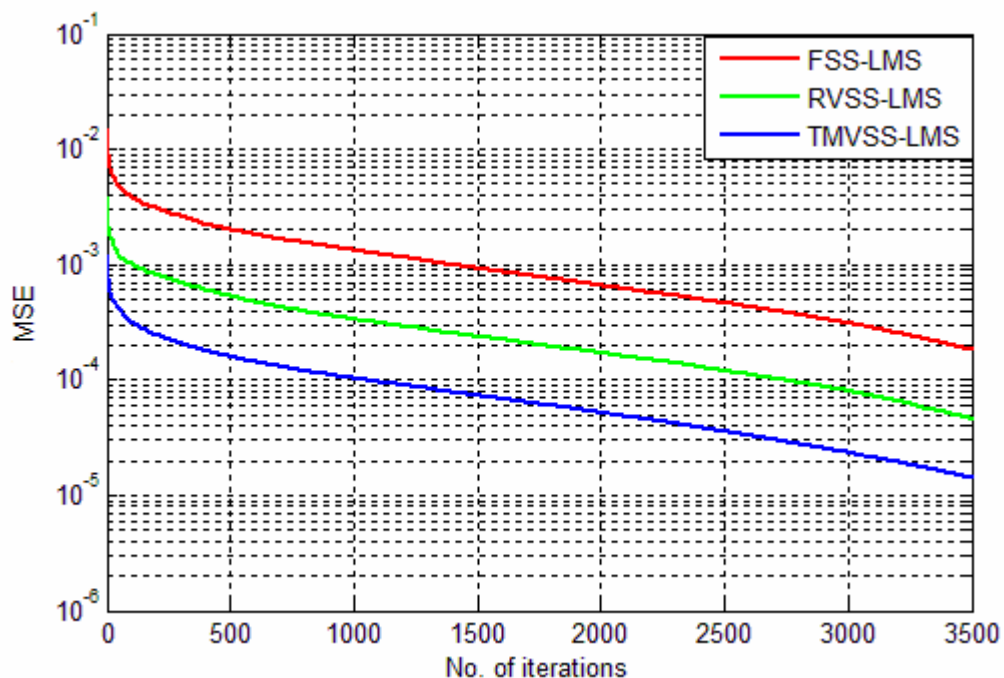


Figure 3.8.2 MSE performance of NAEC using AR(1) input signal (with correlation coefficient  $\bar{\rho}_{c0} = 0.1$ )

Figure 3.8.2 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS algorithms for AR(1) input case with correlation coefficient equal to 0.1, which are used for updating sigmoid parameter values.

At 500<sup>th</sup> iteration, for the AR(1) input signaling waveform with  $\bar{\rho}_{c_0} = 0.1$ , it is observed from outcomes presented in Figure 3.8.2 that the TMVSS-LMS and RLS algorithm based NAEC performs approximately 5.24 dB better than the RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance benefit of former increases to approximately 10.98 dB in comparison to the FSS-LMS and RLS algorithm based NAEC.

The MSE outcomes in Figure 3.8.2 manifest that for AR(1) input signaling waveform with correlation coefficient equal to 0.1, overall MSE is highest in case of FSS-LMS and RLS algorithm based NAEC and least in case of the TMVSS-LMS and RLS algorithm based NAEC. It is due to the step-size parameter, which remains same in the FSS-LMS case, used for the sigmoid parameter updating. All the three adaptive algorithms used for updating of sigmoid parameters converge at different rates, as inferred from the Figure 3.8.2. It is also observed from the figure that TMVSS-LMS algorithm converges in approximately 500 iterations, while other two algorithms take more number of iterations for convergence to the same point.

From the close observation, it is also apparent that the value of MSE is small in case of AR(1) input signaling waveform with correlation parameter equal to 0.1 as compared to the case of Gaussian signal given as input to the NAEC, for all three algorithms based NAECs, which are used for updating of sigmoid parameters. This is due to the strong correlation between input samples in AR(1) signal, which is not present in the case of Gaussian signal. Based on results in Figure 3.8.1 and Figure 3.8.2, the best results are obtained for the TMVSS-LMS and RLS algorithm based NAEC, which shows a benefit of approximately 19.28 dB, in terms of MSE factor, when the AR(1) input signal with  $\bar{\rho}_{c_0} = 0.1$  is used, as compared to the Gaussian input signal, at 500<sup>th</sup> iteration.

### Case 3.8.3:- MSE Performance of NAEC Using AR(1) Input Signaling Waveform with Correlation Coefficient Equal to 0.9

In this case, MSE performance of the nonlinear acoustic echo canceller is evaluated using the Equation (3.29). The MSE data in the graph is plotted on the linear scale.

In this case, AR(1) signal [38], [39] with correlation coefficient  $\bar{\rho}_{c_0} = 0.9$  is given as input to the presented NAEC. The AR(1) signal is obtained by using the equation, which is expressed as

$x(n) = \bar{\rho}_{c0}x(n-1) + \bar{v}(n)$ ; where,  $\bar{\rho}_{c0}$  denotes AR(1) coefficient or correlation coefficient. The variance of input signal is set at unity i.e.,  $\sigma_x^2 = 1$  with zero-mean; and the statistics of white Gaussian noise  $\bar{v}(n)$  are set as  $\sigma_v^2 = \sigma_x^2(1 - \bar{\rho}_{c0}^2)$  with zero-mean.

The value of variance  $\sigma_v^2$  is equal to 0.19, when  $\bar{\rho}_{c0} = 0.9$ .

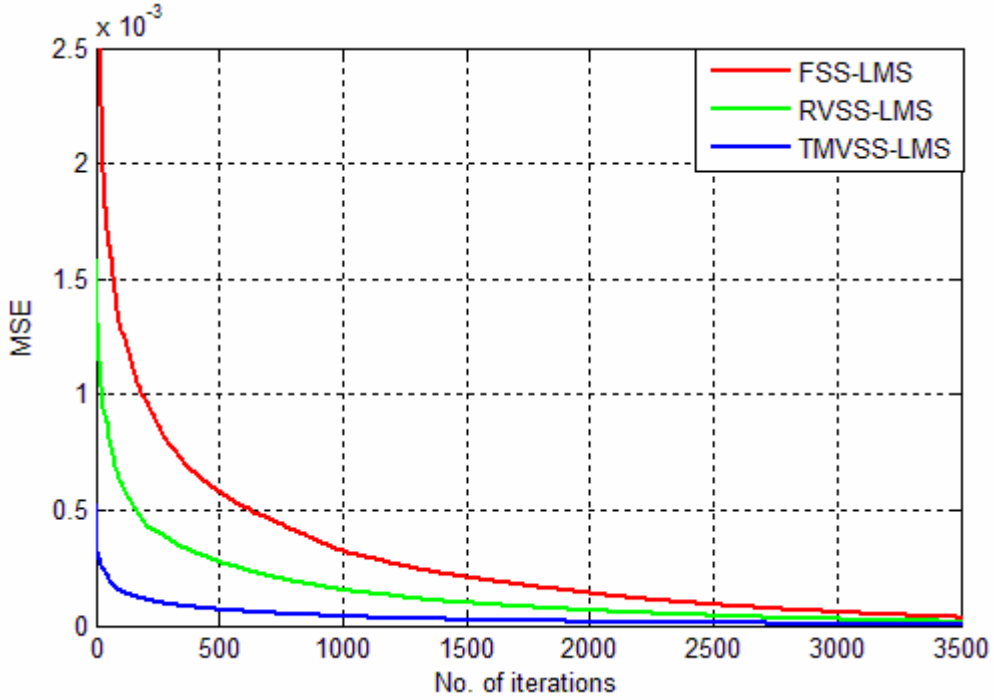


Figure 3.8.3 MSE performance of NAEC using AR(1) input signaling waveform (with correlation parameter  $\bar{\rho}_{c0} = 0.9$ )

Figure 3.8.3 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS algorithms for AR(1) input signaling waveform case with correlation parameter equal to 0.9, which are used for updating sigmoid parameter values.

At 500<sup>th</sup> iteration, for the AR(1) input signaling waveform with  $\bar{\rho}_{c0} = 0.9$ , it is observed from outcomes presented in Figure 3.8.3 that the TMVSS-LMS and RLS algorithm based NAEC performs approximately 6.03 dB better than RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance advantage of former increases to approximately 9.26 dB in comparison to the FSS-LMS and RLS algorithm based NAEC.

The MSE outcomes in Figure 3.8.3 manifest that for AR(1) input signaling waveform with correlation coefficient equal to 0.9, overall MSE is highest in case of the FSS-LMS and RLS algorithm based NAEC and least in case of the TMVSS-LMS and RLS algorithm based NAEC. It is also apparent from the Figure 3.8.3 that the TMVSS-LMS algorithm converges

at approximately 500 iterations, while other two takes algorithms more number of iterations for convergence to the same point.

From the close observation, it is also inferred that the value of MSE is small in case of the AR(1) input signaling waveform with correlation parameter equal to 0.9 as compared to the AR(1) input signaling waveform with correlation coefficient equal to 0.1, and the Gaussian signal given as input to the NAEC, in all three algorithms used for updating of sigmoid parameters. It is due to the strong correlation between successive input sample values in AR(1) signal with  $\bar{\rho}_{c0} = 0.9$ , which is weak in case of the AR(1) signal with  $\bar{\rho}_{c0} = 0.1$ , and not present in case of Gaussian signal. Based on the observations shown in Figures 3.8.1 – 3.8.3, the TMVSS-LMS and RLS algorithm based NAEC provides best results. It has an advantage of approximately 3.66 dB, in terms of MSE factor when AR(1) input signaling waveform with  $\bar{\rho}_{c0} = 0.9$  is used as compared to the AR(1) input signaling waveform with  $\bar{\rho}_{c0} = 0.1$ , and this advantage increases to approximately 22.94 dB as compared to the Gaussian input signal, at 500<sup>th</sup> iteration.

#### Case 3.8.4:- MSE Performance of NAEC Using AR(2) Input Signal

In this case, MSE performance of the NAEC is evaluated using the Equation (3.29). The MSE data in the graph is plotted on the linear scale.

In this case, the AR(2) signal [30], [40], [41] is given as input to the NAEC. The AR(2) signal is obtained by using the equation, which is represented as

$$x(n) = -\bar{\rho}_{c1}x(n-1) - \bar{\rho}_{c2}x(n-2) + \bar{w}(n)$$

where,  $\bar{\rho}_{c1}$  and  $\bar{\rho}_{c2}$  denote the AR(2) coefficients, the values of AR(2) coefficients are set as  $\bar{\rho}_{c2} = 0.9$ ,  $\bar{\rho}_{c1} = -0.2$ , and  $\bar{w}(n)$  is white Gaussian noise exhibiting mean  $m_{\bar{w}} = 0$ , where variance  $\sigma_{\bar{w}}^2$  is obtained as

$$\sigma_{\bar{w}}^2 = \frac{(1 - \bar{\rho}_{c2})}{(1 + \bar{\rho}_{c2})} \left[ (1 + \bar{\rho}_{c2})^2 - \bar{\rho}_{c1}^2 \right]$$

The value of this variance is calculated to be  $\sigma_{\bar{w}}^2 = 0.188$ . In the case of AR(2) signal, the present input sample value depends upon the past two input sample values.

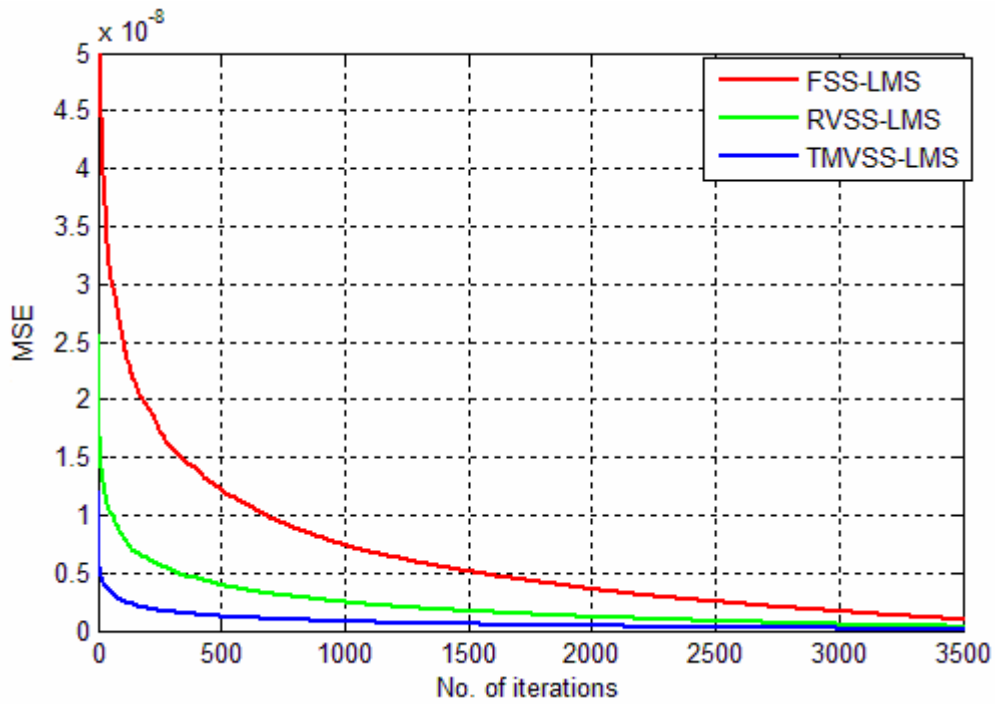


Figure 3.8.4 MSE performance of NAEC using AR(2) input signal

Figure 3.8.4 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS algorithms for AR(2) input signal case, which are used for updating sigmoid parameter values.

At 500<sup>th</sup> iteration, for the AR(2) input signal, it is observed from outcomes presented in Figure 3.8.4 that the TMVSS-LMS and RLS algorithm based NAEC performs approximately 5.1 dB better than RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance benefit of former increases to approximately 10.03 dB in comparison to the FSS-LMS and RLS algorithm based NAEC.

The MSE outcomes in Figure 3.8.4 manifest that for AR(2) input signal, the overall MSE is highest in case of the FSS-LMS and RLS algorithm based NAEC and least in case of TMVSS-LMS and RLS algorithm based NAEC. It is also observed from the figure that the TMVSS-LMS algorithm converges in approximately 500 iterations while other two algorithms take more number of iterations for convergence to the same point.

From the close observation, it is also apparent that the value of the MSE is very-very small in case of the AR(2) input signal as compared to both AR(1) signals (whether strongly correlated or weakly correlated) i.e., with correlation coefficient equal to 0.9 and 0.1 respectively and the Gaussian signal as input signal to the NAEC for three algorithms used for updating the sigmoid parameters. This is due to very strong correlation between input signal samples or in other words due to the dependence of the present input sample upon the past two input sample values, in case of AR(2) input signal. The TMVSS-LMS and RLS

algorithm based NAEC gives best results among all. Based on outcomes detailed in Figures 3.8.1 – 3.8.4, it exhibits a benefit of approximately 47.53 dB, in terms of MSE factor, when the AR(2) input signal is used as compared to the AR(1) signal with  $\bar{\rho}_{c_0} = 0.9$ . This benefit increases to approximately 51.16 dB as compared to the AR(1) signal with  $\bar{\rho}_{c_0} = 0.1$ , and this advantage further increases to approximately 70.47 dB as compared to the Gaussian input signal, at 500<sup>th</sup> iteration.

Therefore from all the aforementioned cases, it is observed that for updating the parameters of sigmoid transformation function, the TMVSS-LMS algorithm is best as compared to other two adaptive procedures in terms of convergence speed as well as MSE factor value. To estimate the coefficient vector of the tapped-delay-line filter, the RLS procedure is better in comparison to the NLMS procedure; this is because of its fast convergence rate and low level misadjustment. So as whole, the TMVSS-LMS and RLS algorithm based NAEC performs better as compared to other algorithm based NAEC, in terms of ERLE as well as MSE factors.

It is also concluded that for all the four input cases considered in this chapter, the AR(2) signal gives lowest value of MSE as compared to all other three cases. This is due to the existence of very strong correlation between the present input signaling sample and past two input signaling samples.

**CHAPTER 4**

**NONLINEAR ACOUSTIC ECHO CANCELLATION  
TECHNIQUE USING VSS-LMS AND RLS ALGORITHM**

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*In this chapter, we present a brief review on the performance criterion of presented nonlinear acoustic echo canceller, which utilizes a nonlinear sigmoid transformation function in combination with tapped-delay-line FIR filter to suppress the nonlinear constituents of the acoustic echo under noisy environment. These components are not suppressed by using linear acoustic echo cancellers. In this chapter, we will focus on the echo-return-loss-enhancement (ERLE) as well as mean-squared-error (MSE) calculation of presented NAEC for different types of input signals separately, and also compare their performance while using FSS-LMS, RVSS-LMS, TMVSS-LMS, NLMS and RLS algorithms.*

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**4.1 NAEC USING SIGMOID-TYPE TRANSFORMATION FUNCTION REPRESENTING NONLINEARITY**

In this research work, an easy yet efficient nonlinear echo cancellation technique is reported, which uses an adaptable sigmoid-type characteristic function unit [18], [34] with a tapped-delay-line FIR filter. This scheme uses the variable-step-size (VSS) least-mean-square (LMS) procedure for updating parameters of nonlinear sigmoid transformation function and RLS procedure to estimate the coefficient vector of tapped-delay-line FIR filter. This sigmoid transformation function is used to eliminate the effects that occurred because of nonlinearities of amplifiers/loudspeakers [18]. The benefit of sigmoid transformation function is that it can adapt its parameters for both hard as well as soft clipping nonlinearities, and offers superior performance in comparison to Volterra series based filters. The simple equation of sigmoid characteristic for tracking purpose is represented as

$$\phi\{x(n)\} = \frac{2\bar{\beta}_n}{1 + e^{(-\bar{\alpha}_n x(n))}} - \bar{\beta}_n \quad (4.1)$$

where,  $x(n)$  is the input given to NAEC and loudspeaker both, which is represented as

$\bar{x}(n) = [x(n), x(n-1), \dots, x(n-M+1)]^T$ . Here,  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  are the parameters of sigmoid function, which are tracked by using various VSS-LMS algorithms. When  $\bar{\alpha}_n \rightarrow \bar{\alpha}$  and  $\bar{\beta}_n \rightarrow \bar{\beta}$ , then  $\phi \rightarrow f$ .

Here,  $f$  is same as represented in Equation (3.2).

$\bar{\alpha}$  and  $\bar{\beta}$  are the parameters of sigmoid-type nonlinear transformation function.  $\bar{\alpha}$  determines the shape of saturation curve of the loudspeaker and  $\bar{\beta}$  determines the clipping value of saturation curve. The idea is to update parameters of nonlinear sigmoid function by using various versions of VSS-LMS procedure, such that the unknown nonlinear distortion of amplifier is perfectly matched, thereby cancelling nonlinear distortions, which can't be cancelled by the usage of linear AECs. The figure of presented nonlinear acoustic echo canceller is demonstrated in Figure 4.1.

The echo recorded by microphone under noisy environment is expressed as

$$d(n) = y(n) + \eta(n) \quad (4.2)$$

Let  $\eta(n)$  be the AWGN signal with variance  $\sigma_\eta^2$  and mean zero.

The output of adaptive filtering configuration using adaptive procedure is represented as follows

$$\hat{y}(n) = \phi\{x(n)\} * h(n)$$

It can also be written as

$$\hat{y}(n) = \vec{h}^T(n) \phi\{\vec{x}(n)\} \quad (4.3)$$

where,  $\vec{h}(n)$  is impulse response coefficient vector of adaptive filter, such that

$$\vec{h}(n) = [h(0;n), h(1;n), \dots, h(M-1;n)]^T \quad (4.4)$$

$\phi\{\vec{x}(n)\}$  is expressed as

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

Let  $u(n) = \phi(x(n))$ , which is represented as follows

$$\vec{u}(n) = [u(n), u(n-1), \dots, u(n-M+1)]^T \quad (4.5)$$

The error signal is evaluated as

$$\begin{aligned} \varepsilon(n) &= \{y(n) - \hat{y}(n)\} + \eta(n) \\ &= d(n) - \hat{y}(n) \\ &= d(n) - \vec{h}^T(n) \vec{u}(n) \end{aligned} \quad (4.6)$$

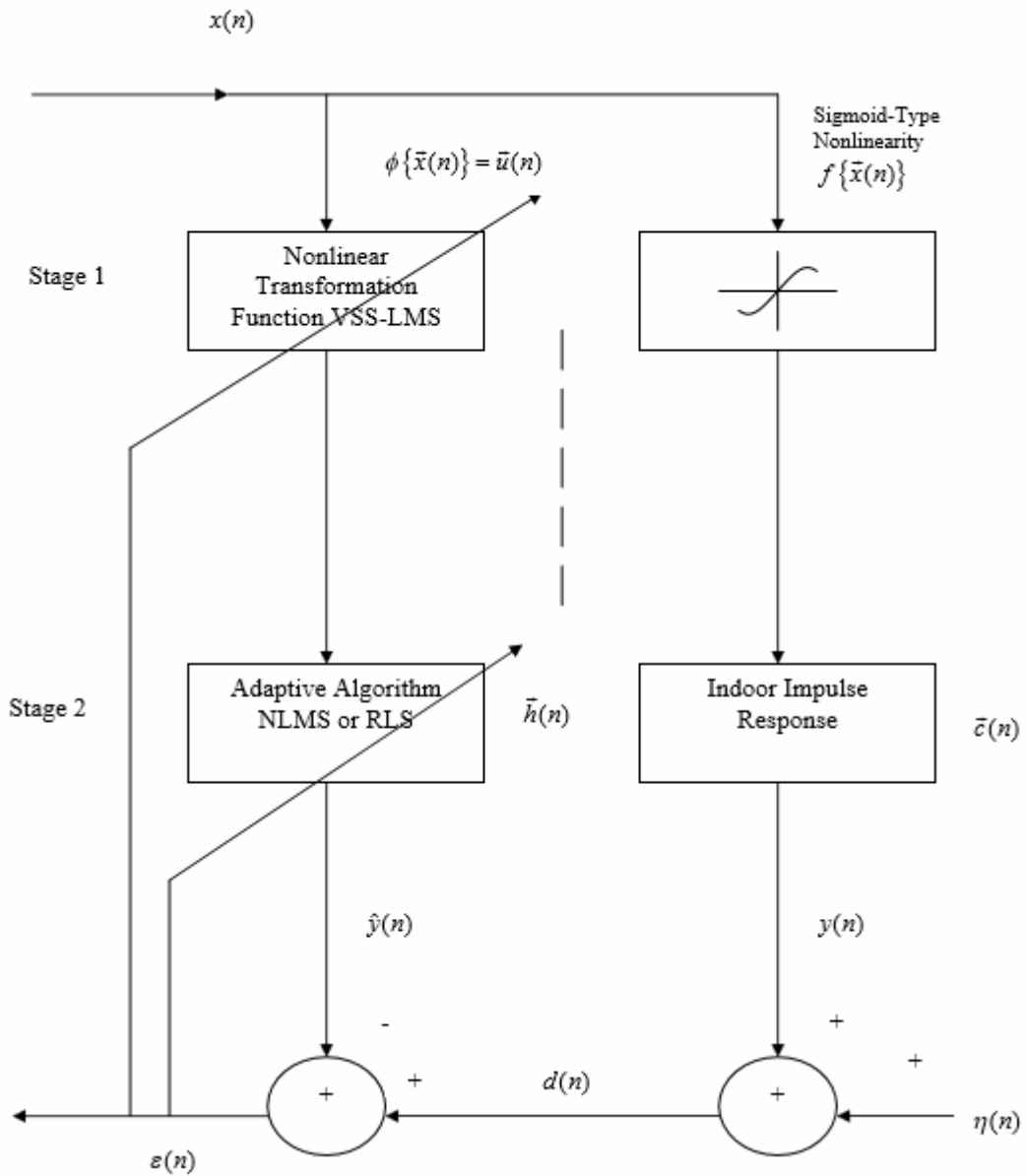


Figure 4.1 Presented nonlinear acoustic echo canceller

Using Equations (4.3) - (4.5), we obtain

$$\hat{y}(n) = \vec{h}^T(n) \vec{u}(n)$$

$$= [h(0;n), h(1;n), \dots, h(M-1;n)] \begin{bmatrix} u(n) \\ u(n-1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ u(n-M+1) \end{bmatrix}$$

$$\begin{aligned}
&= h(0;n)u(n) + h(1;n)u(n-1), + \dots + h(M-1;n)u(n-M+1) \\
&= \sum_{k=0}^{M-1} h(k;n)u(n-k)
\end{aligned} \tag{4.7}$$

where,  $\vec{h}(n)$  is the tapped-delay-line FIR filter coefficient vector, which is to be estimated by utilizing adaptive filtering procedures. There are large number of adaptive procedures utilized for updating the sigmoid feature parameters and for estimating the coefficient vector of tapped-delay-line FIR filter. The algorithms utilized for this motive in this research work are as follows

## 4.2 ALGORITHMS FOR ESTIMATING SIGMOID PARAMETERS

There are various adaptive procedures, which can be utilized for updating the sigmoid parameters. But, LMS algorithm [30] is easy to handle due to its less complexity and less computational burden regardless of its slow convergence. To update the sigmoid parameters, various other types of LMS procedures are utilized in this research work, which are mentioned below

- a) FSS-LMS algorithm [30]
- b) RVSS-LMS algorithm [24]
- c) TMVSS-LMS algorithm [25]

These three algorithms are different from each other on the basis of step-size. The step-size is the factor, by which sigmoid parameter value increases or decreases depending upon the value of the error signal evaluated at that time. In this research work, the effect of different levels of the nonlinearity of the sigmoid function on the performance of presented NAEC is also considered.

### 4.2.1 Fixed Step-size Least Mean Square Algorithm

In FSS-LMS procedure [19], [30], the step-size for both the sigmoid parameters are fixed i.e., it doesn't change at each iteration, which means that the value of step-size for the sigmoid parameters remains same at each iteration. Here,  $\bar{\alpha}$  and  $\bar{\beta}$  are the basic parameters of nonlinear sigmoid transformation function, which are utilized to define the slope as well as clipping value respectively of sigmoid-type nonlinearity.

For FSS-LMS, the values of step-size of sigmoid parameters i.e.,  $\mu_{\bar{\alpha}_n}$  and  $\mu_{\bar{\beta}_n}$  are assumed steady, and it remains same at each iteration, which are considered to be

$$\mu_{\bar{\alpha}_n}(n) = \mu_{\bar{\beta}_n}(n) = \mu_{FSS} = \mu_{MIN} = 10^{-4},$$

The maximum value of the step-size i.e.,  $\mu_{FSSMAX}$  should remain in proper limits that is derived from the simple LMS algorithm convergence situation, which is mentioned below

$$0 < \mu_{FSSMAX} \leq \frac{2}{3tr(\bar{R})} < \frac{2}{\lambda_{MAX}}$$

where,  $\lambda_{MAX}$  is greatest eigenvalue of the covariance matrix  $\bar{R} = E[\bar{x}(n)\bar{x}^T(n)]$ , when mean of  $x(n)$  is zero. The values of the step-size for both sigmoid parameters  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  are made constant, and it remains constant for each iteration. The value of step-size for FSS-LMS algorithm for sigmoid parameters is set as

$$\mu_{FSS} = \mu_{MIN}$$

Subsequently, the same value of  $\mu_{MIN}$  is used in RVSS-LMS and TMVSS-LMS procedures.

From Equation (4.6), the mean-squared-error (MSE) is obtained as

$$J_L(n) = E\{|\varepsilon(n)|^2\} \quad (4.8)$$

in Equation (4.8), the total parameters unknown is equal to three, which are  $\bar{\alpha}_n$ ,  $\bar{\beta}_n$  and  $\bar{h}(n)$ .

The FSS-LMS procedure is used to find optimal solution for  $\bar{\alpha}_n$  and  $\bar{\beta}_n$ , which leads to following update formulas

$$\begin{aligned} \bar{\alpha}_{n+1} &= \bar{\alpha}_n(n) - \frac{\mu_{\bar{\alpha}}}{2} \frac{\partial J_L(n)}{\partial \bar{\alpha}} \Big|_{\bar{\alpha}=\bar{\alpha}_n; \bar{\beta}=\bar{\beta}_n} \\ &= \bar{\alpha}_n(n) + \mu_{\bar{\alpha}} \varepsilon(n) \bar{h}^T(n) \frac{\partial \bar{u}(n)}{\partial \bar{\alpha}} \Big|_{\bar{\alpha}=\bar{\alpha}_n; \bar{\beta}=\bar{\beta}_n} \end{aligned} \quad (4.9)$$

Here,  $\frac{\partial \bar{u}(n)}{\partial \bar{\alpha}}$  is column vector, whose each element is evaluated by utilizing the equation given below

$$\frac{\partial \phi(x)}{\partial \bar{\alpha}} = \frac{2x \exp(-\bar{\alpha}x)}{[1 + \exp(-\bar{\alpha}x)]^2} \bar{\beta} \quad (4.10)$$

with

$$\phi(x) = u = \frac{2\bar{\beta}}{1 + \exp(-\bar{\alpha}x)} - \bar{\beta}$$

Similarly for  $\bar{\beta}$ , the equations are given below

$$\begin{aligned} \bar{\beta}_{n+1} &= \bar{\beta}_n(n) - \frac{\mu_{\bar{\beta}}}{2} \frac{\partial J_L(n)}{\partial \bar{\beta}} \Big|_{\bar{\alpha}=\bar{\alpha}_n; \bar{\beta}=\bar{\beta}_n} \\ &= \bar{\beta}_n(n) + \mu_{\bar{\beta}} \varepsilon(n) \bar{h}^T(n) \frac{\partial \bar{u}(n)}{\partial \bar{\beta}} \Big|_{\bar{\alpha}=\bar{\alpha}_n; \bar{\beta}=\bar{\beta}_n} \end{aligned} \quad (4.11)$$

Here,  $\frac{\partial \vec{u}(n)}{\partial \beta}$  is column vector, whose each element is evaluated by utilizing the equation given below

$$\frac{\partial \phi(x)}{\partial \beta} = \frac{2}{1 + \exp(-\bar{\alpha}x)} - 1 \quad (4.12)$$

The convergence rate of this FSS-LMS procedure is very slow and MSE value is also high. In order to increase the convergence rate, VSS-LMS [24], [25] algorithm can be used for updating the parameters of sigmoid transformation function.

#### 4.2.2 Robust Variable Step-size Least Mean Square Algorithm

Majority of the applications make use of LMS procedure with a constant step-size. The choice of step-size reflects a tradeoff between misadjustment and speed of adaptation. Subsequent research work describes the issue of optimization of step-size or the techniques to vary step-size to enhance performance [24]. In [24] an idea of a variable step-size algorithm that is simple to incorporate and is capable of providing both fast tracking as well as low misadjustment, is presented by Kwong and Johnston.

In the RVSS-LMS, the values of step-size for both  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  i.e.,  $\mu_{\bar{\alpha}_n}(n)$  and  $\mu_{\bar{\beta}_n}(n)$  are made variable i.e., that varies at each iteration (either increases or decreases) depending upon the value of error signal i.e.,  $\varepsilon(n)$  at that time, but the maximum and minimum values of both  $\mu_{\bar{\alpha}_n}(n)$  and  $\mu_{\bar{\beta}_n}(n)$  are kept constant, so that both of them remains in proper limits, which are fixed as according to conditions given in [24].

The VSS-LMS procedure is utilized to find the optimal solution of  $\bar{\alpha}_n$  and  $\bar{\beta}_n$ , resulting in update formulas, which are mentioned below

$$\begin{aligned} \bar{\alpha}_{n+1} &= \bar{\alpha}_n(n) - \frac{\mu_{\bar{\alpha}_n}(n)}{2} \frac{\partial J_L(n)}{\partial \bar{\alpha}} \Big|_{\bar{\alpha}=\bar{\alpha}_n; \bar{\beta}=\bar{\beta}_n} \\ &= \bar{\alpha}_n(n) + \mu_{\bar{\alpha}_n}(n) \varepsilon(n) \vec{h}^T(n) \frac{\partial \vec{u}(n)}{\partial \bar{\alpha}} \Big|_{\bar{\alpha}=\bar{\alpha}_n; \bar{\beta}=\bar{\beta}_n} \end{aligned} \quad (4.13)$$

Here,  $\frac{\partial \vec{u}(n)}{\partial \bar{\alpha}}$  is column vector, whose each element is evaluated by using

$$\frac{\partial \phi(x)}{\partial \bar{\alpha}} = \frac{2x \exp(-\bar{\alpha}x)}{[1 + \exp(-\bar{\alpha}x)]^2} \bar{\beta} \quad (4.14)$$

with

$$\phi(x) = u = \frac{2\bar{\beta}}{1 + \exp(-\bar{\alpha}x)} - \bar{\beta}$$

Similarly for  $\bar{\beta}$ , the equations are

$$\begin{aligned}
\bar{\beta}_{n+1} &= \bar{\beta}_n(n) - \frac{\mu_{\bar{\beta}}(n)}{2} \frac{\partial J_L(n)}{\partial \bar{\beta}} \Big|_{\bar{\alpha}=\bar{\alpha}_n, \bar{\beta}=\bar{\beta}_n} \\
&= \bar{\beta}_n(n) + \mu_{\bar{\beta}}(n) \varepsilon(n) \bar{h}^T(n) \frac{\partial \bar{u}(n)}{\partial \bar{\beta}} \Big|_{\bar{\alpha}=\bar{\alpha}_n, \bar{\beta}=\bar{\beta}_n}
\end{aligned} \tag{4.15}$$

Here,  $\frac{\partial \bar{u}(n)}{\partial \bar{\beta}}$  is column vector, whose each element is evaluated by utilizing the equation as

$$\frac{\partial \phi(x)}{\partial \bar{\beta}} = \frac{2}{1 + \exp(-\bar{\alpha}x)} - 1 \tag{4.16}$$

For RVSS-LMS algorithm the values of  $\mu_{\bar{\alpha}_n}(n)$  and  $\mu_{\bar{\beta}_n}(n)$ , which are updated at each iteration are derived from the following equations

$$\mu_{RVSS}(n+1) = \left\{ \begin{array}{ll} \mu_{RVSSMAX} & \text{if } \mu_{RVSS}(n) > \mu_{RVSSMAX} \\ \mu_{RVSSMIN} & \text{if } \mu_{RVSS}(n) < \mu_{RVSSMIN} \\ \mu_{RVSS}(n) & \text{otherwise} \end{array} \right\} \tag{4.17}$$

$$\mu_{RVSS}(n+1) = \alpha_{RVSS} \mu_{RVSS}(n) + \gamma_{RVSS} \varepsilon_{RVSS}^2(n) \tag{4.18}$$

where,  $0 < \alpha_{RVSS} < 1$  and  $1 > \gamma_{RVSS} > 0$  are adjusted to have minimum possible misadjustment. The  $\alpha_{RVSS}$  and  $\gamma_{RVSS}$  are the parameters of RVSS-LMS procedure. The initial step-size is usually taken to be  $\mu_{RVSSMAX}$  although this procedure is not sensitive to the choice. The step-size is always positive and is controlled by the value of prediction error  $\varepsilon(n)$  and the parameters  $\alpha_{RVSS}$  and  $\gamma_{RVSS}$ . Intuitively speaking, a large prediction error increases the step-size to provide faster tracking. If the prediction error decreases, the step-size decreases to alleviate the misadjustment. The constant  $\mu_{RVSSMAX}$  is chosen to ensure that the MSE of the algorithm remains bounded. For RVSS-LMS algorithm, the values of  $\mu_{RVSSMAX}$  and  $\mu_{RVSSMIN}$  for both  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  are set according to Equation (4.17); such that

$$\mu_{RVSSMIN} = \mu_{FSS} = \mu_{MIN} \text{ and } 0 < \mu_{RVSSMAX} \leq \frac{2}{3tr(\bar{R})}, \text{ where } \bar{R} \text{ is the covariance matrix given as}$$

$$\bar{R} = E[\bar{x}(n)\bar{x}^T(n)], \text{ when mean of } x(n) \text{ is zero.}$$

#### 4.2.3 Modified Variable Step-size Least Mean Square Algorithm

The FSS-LMS and RVSS-LMS procedure works efficiently for updating the sigmoid parameter values, but the experimentation of these procedures depicts that their performance is highly sensitive to noise disturbances. The TMVSS-LMS procedure yields fast

convergence at early stages of adaptation, while ensuring low final misadjustment. The performance of this procedure is not affected by existing uncorrelated noise disturbances.

In TMVSS-LMS, the values of step-size of both  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  i.e.,  $\mu_{\bar{\alpha}_n}(n)$  and  $\mu_{\bar{\beta}_n}(n)$  are made variable i.e., that varies at each iteration (either increases or decreases) depending upon the value of MSE at each iteration same as RVSS-LMS. However in TMVSS-LMS procedure [25], step-size of algorithm is tuned in accordance with square of time-averaged estimate of the autocorrelation of  $\varepsilon(n)$  and  $\varepsilon(n-1)$  i.e., error signals. In this case also, the maximum and minimum values of both  $\mu_{\bar{\alpha}_n}$  and  $\mu_{\bar{\beta}_n}$  are fixed, so that both of them remains in proper limits, which are fixed as according to conditions given in [25]. To find the optimal solution of  $\bar{\alpha}_n$  and  $\bar{\beta}_n$ , same equations are utilized as used in RVSS-LMS algorithm. But in this case, the values of  $\mu_{\bar{\alpha}_n}(n)$  and  $\mu_{\bar{\beta}_n}(n)$ , which are updated at each iteration, are derived from the condition given in following equations

$$\mu_{TMVSS}(n+1) = \begin{cases} \mu_{TMVSSMAX} & \text{if } \mu_{TMVSS}(n) > \mu_{TMVSSMAX} \\ \mu_{TMVSSMIN} & \text{if } \mu_{TMVSS}(n) < \mu_{TMVSSMIN} \\ \alpha_{TMVSS}\mu_{TMVSS}(n) + \gamma_{TMVSS}q_{TMVSS}^2(n) & \text{otherwise} \end{cases} \quad (4.19)$$

$$q_{TMVSS}(n+1) = \beta_{TMVSS}q_{TMVSS}(n) + (1 - \beta_{TMVSS})\varepsilon_{TMVSS}(n+1)\varepsilon_{TMVSS}(n) \quad (4.20)$$

where,  $0 < \alpha_{TMVSS} < 1$ ,  $1 > \gamma_{TMVSS} > 0$  and  $0 < \beta_{TMVSS} < 1$  are adjusted to have minimum possible misadjustment. The  $\alpha_{TMVSS}$ ,  $\gamma_{TMVSS}$  and  $\beta_{TMVSS}$  are parameters of TMVSS-LMS procedure. The constant  $\mu_{TMVSSMAX}$  is normally chosen near the point of instability of FSS-LMS to impart maximum possible convergence rate. The condition to update values of  $\mu_{\bar{\alpha}_n}(n)$  and  $\mu_{\bar{\beta}_n}(n)$  in TMVSS-LMS is somewhat different from RVSS-LMS. The conditions for  $\mu_{TMVSSMAX}$  and  $\mu_{TMVSSMIN}$  is same as for RVSS-LMS procedure. For TMVSS-LMS procedure the values of  $\mu_{TMVSSMAX}$  and  $\mu_{TMVSSMIN}$  for both  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  are set according to Equation (4.19) and Equation (4.20), given as

$\mu_{TMVSSMIN} = \mu_{FSS} = \mu_{MIN}$  and  $0 < \mu_{TMVSSMAX} \leq \frac{2}{3tr(\bar{R})}$ , where  $\bar{R}$  is the covariance matrix given as  $\bar{R} = E[\bar{x}(n)\bar{x}^T(n)]$ , when mean of  $x(n)$  is zero.

#### 4.2.4 Algorithms for Estimating the Coefficient Vector of Tapped-Delay-Line FIR Filter

Like sigmoid parameter updating, there are various adaptive algorithms, which can be utilized for estimation of the coefficient vector of the tapped-delay-line FIR filter. To estimate the coefficient vector of tapped-delay-line filter, adaptive procedures utilized in this research work are

- a) NLMS algorithm (normalized-least-mean-square)
- b) RLS algorithm (recursive-least-square)

#### 4.2.5 Normalized Least Mean Square Algorithm

In the NLMS algorithm [19], [30], [31], to estimate the values of the coefficient vector of tapped-delay-line FIR filter  $\vec{h}(n)$ , the following equation is utilized

$$\vec{h}(n+1) = \vec{h}(n) + \mu_N \frac{\varepsilon(n)\vec{u}(n)}{c_N + \vec{u}^T(n)\vec{u}(n)} \quad (4.21)$$

where,  $\vec{u}(n) = \phi\{\vec{x}(n)\}$ ,  $\mu_N$  is the step-size and  $\varepsilon(n)$  represents the error signal, which is real in nature. Here, the input signal  $u(n)$  is also real. If input signal is complex in nature then transpose is replaced by Hermitian of input signal vector. The  $\mu_N$  is fixed in NLMS algorithm [8], [31].

The regularization factor  $c_N$  is used for proper working of the NLMS algorithm. It is used so that the denominator of NLMS algorithm must not become '0', otherwise the NLMS algorithm fails.

#### 4.2.6 Recursive Least Square Algorithm

In this case, the RLS algorithm [19], [20], [29], [30], which incorporates the noise characteristics (variance) in its equations, is utilized for the estimation and updating of the weight vector  $\vec{h}(n)$  of the tapped-delay-line FIR filter. This is because of its fast convergence rate. However, RLS procedure working under noisy environment can be briefly detailed as follows

Let cost function for the RLS algorithm under noise [29], [32] is represented as

$$J_R(n) = \sum_{i=M}^n \frac{[\lambda_R(n)]^{n-i} |\varepsilon(i)|^2}{\sigma_\eta^2} \quad (4.22)$$

$e(n) = d(n) - \vec{h}^T(n-1)\vec{u}(n)$ , which is *a priori* estimation error signal.

where,

$$\bar{u}(n) = \phi\{\bar{x}(n)\}$$

$$\text{Let } \bar{\theta}(n) = \bar{P}(n-1)\bar{u}(n)$$

$$\begin{aligned} \bar{K}(n) &= \frac{\bar{P}(n-1)\bar{u}(n)}{\lambda_R(n)\sigma_\eta^2 + \bar{u}^T(n)\bar{P}(n-1)\bar{u}(n)} \\ &= \frac{\bar{\theta}(n)}{\lambda_R(n)\sigma_\eta^2 + \bar{u}^T(n)\bar{\theta}(n)} \end{aligned} \quad (4.23)$$

$$\bar{P}(n) = \frac{1}{\lambda_R(n)} \left[ \bar{P}(n-1) - \bar{K}(n)\bar{u}^T(n)\bar{P}(n-1) \right] \quad (4.24)$$

$$\bar{h}(n) = \bar{h}(n-1) + \bar{K}(n)e(n) \quad (4.25)$$

where,  $\lambda_R$  is a small positive constant (forgetting factor) very close to 1, but smaller than 1,  $\delta$  is the regularizing parameter for RLS algorithm.

*A posteriori* estimate of  $\bar{c}(n)$  is evaluated by using the following equations

$$\bar{h}(0) = \text{null vector}$$

$$\bar{P}(0) = \delta^{-1}I$$

Here,  $\delta$  is kept small for high SNR values and set high for low SNR values.

In this case, AWGN signal is having mean '0' and variance ' $\sigma_\eta^2$ '. As the characteristics of noise are considered in the modelling of RLS, therefore it has more advantages in comparison to traditional RLS procedure [19], [20], [29], [30] and NLMS procedure [19], [30], [31] in terms of both MSE and ERLE factor calculation for the presented NAEC. An additive white Gaussian noise  $\eta(n)$ , which is added to output of echo path  $y(n)$ , therefore the signal-to-noise-ratio (SNR) is defined as

$$SNR = 10 \log_{10} \left( \frac{\sigma_x^2}{\sigma_\eta^2} \right)$$

where,  $\sigma_x^2$  is the variance of input signal, which can also be defined as the power of signal and  $\sigma_\eta^2$  is variance of noise signal.

In this research work, the different types of input signals that are considered are: Gaussian signal [37], AR(1) signal with correlation coefficient  $\bar{\rho}_{c_0} = 0.1$  [38], [39] (weakly correlated), AR(1) signal with correlation coefficient  $\bar{\rho}_{c_0} = 0.9$  [38], [39] (strongly correlated) and AR(2) signal [30], [40], [41].

### 4.3 ECHO RETURN LOSS ENHANCEMENT AND MEAN SQUARED ERROR

To evaluate and compare the performance of presented NAEC, the echo-return-loss-enhancement (ERLE) and mean-squared-error (MSE) are calculated for different types of inputs separately at different values of signal-to-noise-ratio (SNR).

The ERLE is obtained by utilizing the formula

$$ERLE(n)(dB) = 10 \log_{10} \frac{E |d(n)|^2}{E |\varepsilon(n)|^2}$$

which is ensemble-average.

$$ERLE(n)(dB) \approx 10 \log_{10} \left[ \frac{\sum_{j=1}^{250} \{|d(n; j)|^2 / 250\}}{\sum_{j=1}^{250} \{|\varepsilon(n; j)|^2 / 250\}} \right] \quad (4.26)$$

which is time-average, and MSE is calculated as

$$MSE(n) = E[(y(n) + \eta(n) - \vec{h}^T(n)\phi\{\vec{x}(n)\})^2]$$

which is ensemble-average.

$$MSE(n) \approx \sum_{j=1}^{250} \left\{ |d(n; j) - \hat{y}(n; j)|^2 \right\} / 250 \quad (4.27)$$

which is time-average.

### 4.4 SIMULATION RESULTS

We shall compare the performance of FSS-LMS and RLS algorithm based NAEC, RVSS-LMS and RLS algorithm based NAEC and TMVSS-LMS and RLS algorithm based NAEC. The variants of LMS procedure are utilized for updating sigmoid parameters for each input case, and RLS algorithm is utilized for estimation of coefficient vector of the tapped-delay-line FIR filter. The presented outcomes are dependent on ensemble average of 250 independent simulation trials utilizing various types of input signals to the presented NAEC.

For simulation, the number of samples in each input signal vector is taken as  $M=64$ , the length of  $\vec{c}(n)$ , which is the impulse response coefficient vector of room (indoor) i.e., multipath in nature is also considered  $M=64$ .

These coefficients are considered to be static

$$c(k) = \begin{cases} \frac{1}{M}, & 0 \leq k \leq M-1 \\ \text{zero, otherwise} \end{cases} \quad (4.28)$$

The echo generated by the loudspeaker is denoted as

$$y(n) = f \{x(n)\} * c(n) \quad (4.29)$$

where, \* represents the linear convolution operator and Equation (4.29) is also written as

$$y(n) = \bar{c}^T(n) f\{\bar{x}(n)\} \quad (4.30)$$

where,  $f\{\bar{x}(n)\}$  denotes approximately equivalent model of sigmoid-type nonlinearity, and it is same as Equation (3.2).

All simulation trials are performed using MATLAB. In all simulation cases, only single talk case is considered. Note that the mean of each input signal in all simulation trials is set equal to  $m_x = 0$  and variance is set equal to unity in each case i.e.,  $\sigma_x^2 = 1$ . Here, signal-to-noise-ratio is kept at +20 dB by setting the value of  $\sigma_\eta^2 = 0.01$ .

For FSS-LMS procedure, the values of step-size for both sigmoid parameters are set as

$$\mu_{\bar{\alpha}_n}(n) = \mu_{\bar{\beta}_n}(n) = \mu_{FSS} = \mu_{MIN} = 10^{-4}$$

and it remains same for each iteration. For RVSS-LMS algorithm, the values of  $\mu_{RVSSMAX}$  and  $\mu_{RVSSMIN}$  for both  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  are set according to Equation (4.17), and are given below

$$\mu_{RVSSMIN} = \mu_{FSS} = \mu_{MIN} \quad \text{and} \quad \mu_{RVSSMAX} = \frac{2}{3tr(\bar{R})}. \quad \text{The value of } \alpha_{RVSS} \text{ is kept 0.97 and } \gamma_{RVSS} \text{ is set}$$

$8 \times 10^{-4}$  in RVSS-LMS algorithm. The values of  $\mu_{\bar{\alpha}_n}(n)$  and  $\mu_{\bar{\beta}_n}(n)$  are updated according to Equation (4.18).

For TMVSS-LMS algorithm, the values of  $\mu_{TMVSSMAX}$  and  $\mu_{TMVSSMIN}$  for both  $\bar{\alpha}_n$  and  $\bar{\beta}_n$  are set according to Equation (4.19) and Equation (4.20), are given below

$$\mu_{TMVSSMIN} = \mu_{FSS} = \mu_{MIN} \quad \text{and} \quad \mu_{TMVSSMAX} = \frac{2}{3tr(\bar{R})}. \quad \text{The value of } \alpha_{TMVSS} \text{ is kept 0.97 and } \gamma_{TMVSS} \text{ is}$$

set equal to  $8 \times 10^{-4}$ , and  $\beta_{TMVSS}$  is considered equal to 0.97 in TMVSS-LMS procedure. The initial value of  $q(n)$  at the starting point of procedure is set equal to zero (as in [25]).

For estimation of coefficient vector of tapped-delay-line FIR filter, the value of forgetting factor  $\lambda_R$  in RLS procedure is kept 0.97, and the value of regularizing parameter  $\delta^{-1}$  is kept 0.005 in each input case.

The performance evaluation of FSS-LMS and RLS algorithm based NAEC, RVSS-LMS and RLS algorithm based NAEC and TMVSS-LMS and RLS algorithm based NAEC is conducted by carrying out simulation trials, for different types of input signals. The values of sigmoid parameters i.e.,  $\bar{\alpha}$  and  $\bar{\beta}$  in Equation (3.2) for simulation trials in following cases are set equal to 4 and 3 respectively.

#### Case 4.4.1:- MSE Performance of Presented NAEC Using Gaussian Input Signal

In this case, MSE performance of the presented nonlinear acoustic echo canceller is evaluated under noisy environment. The MSE is evaluated by using the Equation (4.27), which is

$$MSE(n) = E[(y(n) + \eta(n) - \vec{h}^T(n)\phi\{\vec{x}(n)\})^2]$$

$$\approx \sum_{j=1}^{250} \left\{ |d(n, j) - \hat{y}(n, j)|^2 \right\} / 250$$

In this case, Gaussian signal [37] is given as input signal to the presented NAEC, which exhibits zero-mean and unity variance.

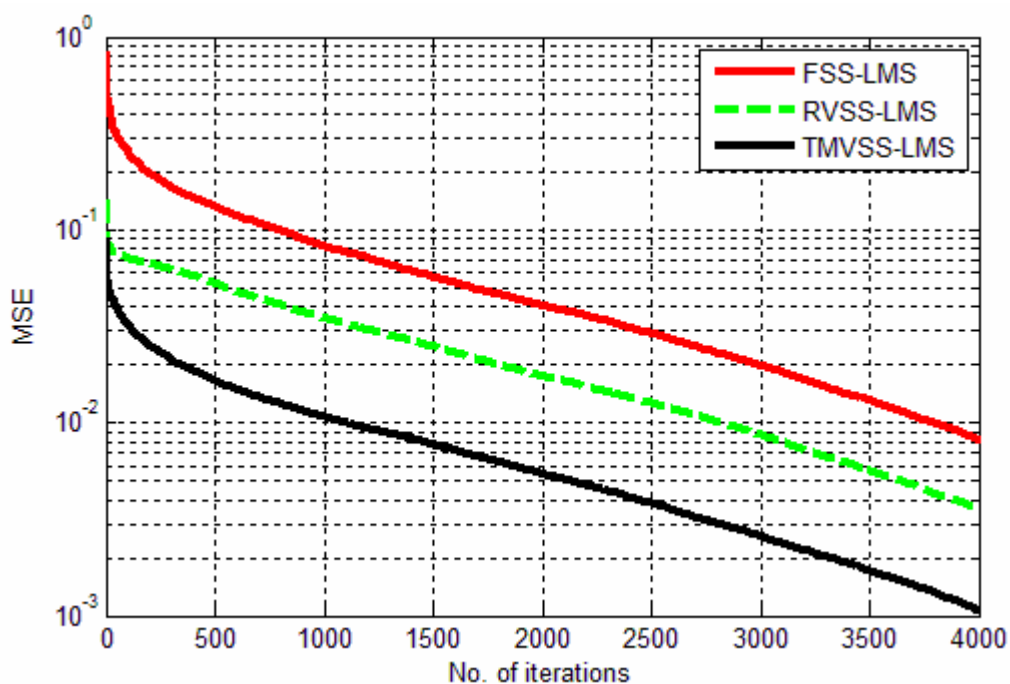


Figure 4.4.1 MSE performance of presented NAEC using Gaussian input

Figure 4.4.1 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS procedures for Gaussian input case, when they are used for sigmoid function parameter estimation, and RLS procedure is used to update FIR filter coefficients.

At 500<sup>th</sup> iteration, for Gaussian input, the MSE readings for presented NAEC are given below

S.No	Type of NAEC	MSE Value (dB) (Approx.)
1.	TMVSS-LMS and RLS algorithm based NAEC	-17.76 dB
2.	RVSS-LMS and RLS algorithm based NAEC	-12.72 dB
3.	FSS-LMS and RLS algorithm based NAEC	-8.73 dB

Table 4.1 MSE Values for Different Types of NAEC Using Gaussian Input Signal

For Gaussian input signal, it is observed from results presented in Figure 4.4.1 and also from the Table 4.1 that at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 5.04 dB better than RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance advantage of former increases to approximately 9.03 dB in comparison to the FSS-LMS and RLS algorithm based NAEC.

Case 4.4.2:- MSE Performance of Presented NAEC Using AR(1) Input Signal with Correlation Coefficient Equal to 0.1

In this case, MSE performance of the presented nonlinear acoustic echo canceller is evaluated under noisy environment. The MSE is evaluated by utilizing the Equation (4.27).

In this case, AR(1) signal [38], [39] with correlation coefficient  $\bar{\rho}_{c_0} = 0.1$  (weakly correlated) is given as input to the presented NAEC. The AR(1) signal is obtained by using the equation, which is given as

$$x(n) = \bar{\rho}_{c_0}x(n-1) + \bar{v}(n)$$

where,  $\bar{\rho}_{c_0}$  denotes the AR(1) coefficient or correlation coefficient, and the value of the correlation coefficient decides the correlation present between the successive samples of AR(1) signal. The  $\bar{v}(n)$ , which is the white Gaussian noise, possesses mean  $m_{\bar{v}} = 0$  and variance is given by

$$\sigma_{\bar{v}}^2 = \sigma_x^2(1 - \bar{\rho}_{c_0}^2)$$

The value of variance  $\sigma_{\bar{v}}^2$  is equal to 0.99, when  $\bar{\rho}_{c_0} = 0.1$ .

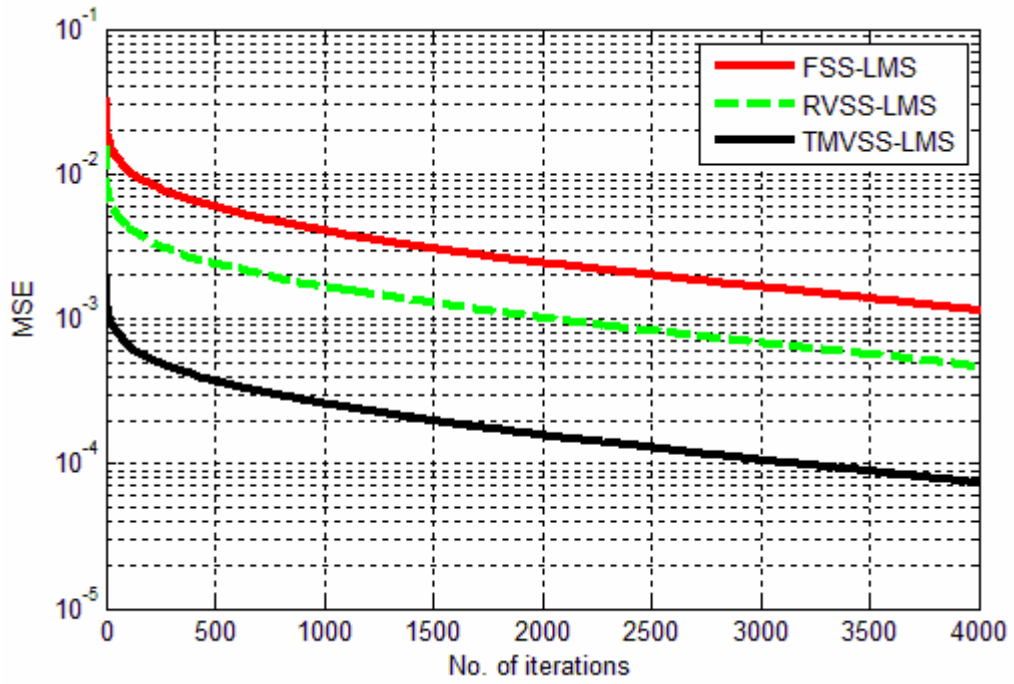


Figure 4.4.2 MSE performance of presented NAEC using AR(1) input  
(with correlation coefficient  $\bar{\rho}_{c_0} = 0.1$ )

Figure 4.4.2 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS procedures for AR(1) input signal with correlation factor equal to 0.1, when these are used for sigmoid function parameter estimation and the RLS procedure is used to update FIR filter coefficients. At 500<sup>th</sup> iteration, for AR(1) input with  $\bar{\rho}_{c_0} = 0.1$  the MSE readings for presented NAEC are mentioned below

S.No	Type of NAEC	MSE Value (dB) (Approx.)
1.	TMVSS-LMS and RLS algorithm based NAEC	-34.28 dB
2.	RVSS-LMS and RLS algorithm based NAEC	-26.20 dB
3.	FSS-LMS and RLS algorithm based NAEC	-22.22 dB

Table 4.2 MSE Values for Different Types of NAEC Using AR(1) Input Signal with  $\bar{\rho}_{c_0} = 0.1$

For AR(1) input signaling waveform with  $\bar{\rho}_{c_0} = 0.1$ , it is observed from results presented in Figure 4.4.2 and also from the Table 4.2 that at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS

algorithm based NAEC performs approximately 8.08 dB better than the RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance advantage of former increases to approximately 12.06 dB in comparison to the FSS-LMS and RLS algorithm based NAEC.

Case 4.4.3:- MSE Performance of Presented NAEC Using AR(1) Input Signaling Waveform with Correlation Parameter Equal to 0.9

In this case, MSE performance of the presented nonlinear acoustic echo canceller is evaluated in the presence of environmental noise. The MSE is evaluated by utilizing the Equation (4.27).

In this case, AR(1) signal [38], [39] with correlation coefficient  $\bar{\rho}_{c_0} = 0.9$  (strongly correlated) is given as input to the presented NAEC. The AR(1) signal is obtained by utilizing the same equation as used in case 4.4.2; only value of the correlation coefficient is set equal to 0.9 in this case. The value of variance  $\sigma_v^2$  is equal to 0.19, when  $\bar{\rho}_{c_0} = 0.9$ .

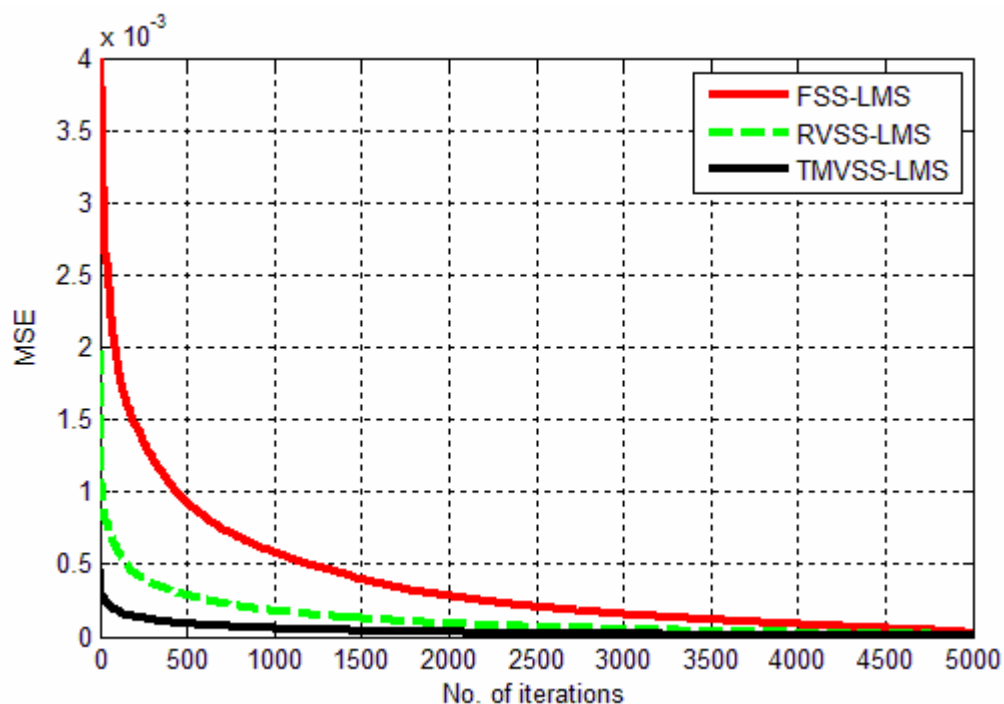


Figure 4.4.3 MSE performance of presented NAEC using AR(1) input (with correlation coefficient  $\bar{\rho}_{c_0} = 0.9$ )

Figure 4.4.3 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS procedures for AR(1) input signal with correlation parameter equal to 0.9, when they are used for sigmoid function parameter estimation and RLS procedure is used to update FIR filter coefficients.

At 500<sup>th</sup> iteration, for AR(1) input with  $\bar{\rho}_{c0} = 0.9$ , the MSE readings for presented NAEC are as follows

S.No	Type of NAEC	MSE Value (dB) (Approx.)
1.	TMVSS-LMS and RLS algorithm based NAEC	-40.55 dB
2.	RVSS-LMS and RLS algorithm based NAEC	-35.35 dB
3.	FSS-LMS and RLS algorithm based NAEC	-30.28 dB

Table 4.3 MSE Values for Different Types of NAEC Using AR(1) Input Signaling Waveform with  $\bar{\rho}_{c0} = 0.9$

For AR(1) input signaling waveform with  $\bar{\rho}_{c0} = 0.9$ , it is observed from results presented in Figure 4.4.3 and also from the Table 4.3 that at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 5.2 dB better than the RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance advantage of former increases to approximately 10.27 dB in comparison to the FSS-LMS and RLS algorithm based NAEC.

#### Case 4.4.4:- MSE Performance of Presented NAEC Using AR(2) Input Signal

In this case, MSE performance of the presented nonlinear acoustic echo canceller is evaluated in the presence of environmental noise. The MSE is evaluated by utilizing the Equation (4.27).

In this case, AR(2) signal [30], [40], [41] is given as input to the presented NAEC. In this case, the present sample value of input signal depends upon the past two input sample values. The AR(2) signal is obtained by utilizing the equation, which is given as

$$x(n) = -\bar{\rho}_{c1}x(n-1) - \bar{\rho}_{c2}x(n-2) + \bar{w}(n)$$

where,  $\bar{\rho}_{c1}$  and  $\bar{\rho}_{c2}$  denote the AR(2) coefficients, and  $\bar{w}(n)$  is white Gaussian noise exhibiting mean  $m_{\bar{w}} = 0$ , the values of AR(2) coefficients are set as  $\bar{\rho}_{c2} = 0.9$ ,  $\bar{\rho}_{c1} = -0.2$ , and its variance is expressed as

$$\sigma_w^2 = \frac{(1 - \bar{\rho}_{c2})}{(1 + \bar{\rho}_{c2})} \left[ (1 + \bar{\rho}_{c2})^2 - \bar{\rho}_{c1}^2 \right]$$

For given coefficient values, it is found that  $\sigma_w^2 = 0.188$ .

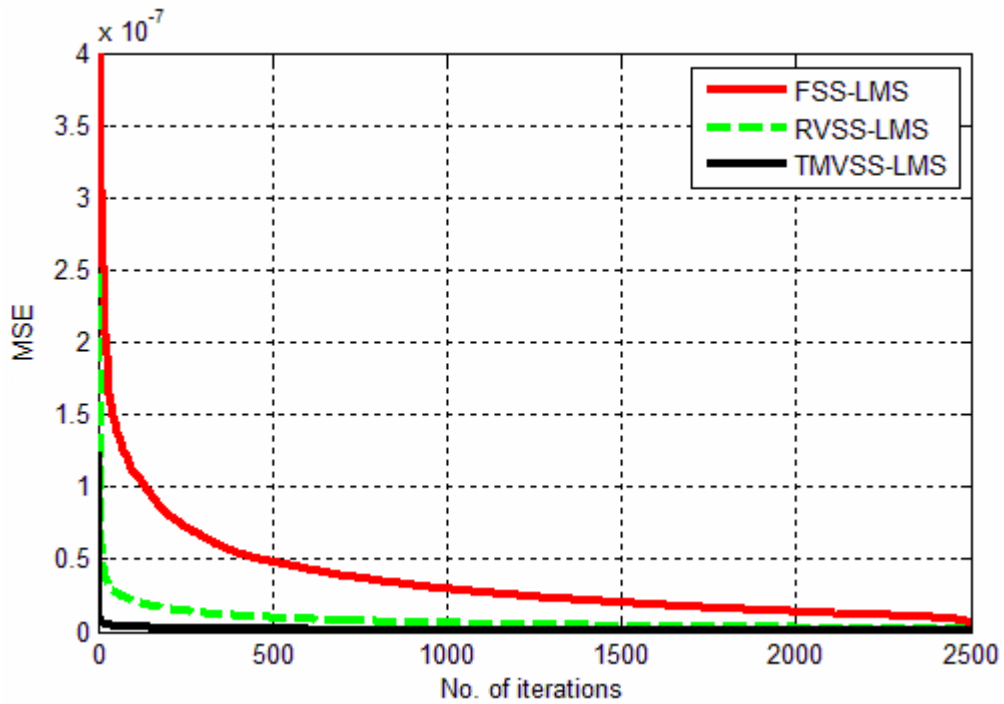


Figure 4.4.4 MSE performance of presented NAEC using AR(2) input

Figure 4.4.4 compares the FSS-LMS, RVSS-LMS and TMVSS-LMS procedures for AR(2) input signal, when they are used for sigmoid function parameter estimation and RLS procedure is used to update FIR filter coefficients. At 500<sup>th</sup> iteration, for AR(2) input, the MSE readings for different algorithm based NAECs are demonstrated as

S.No	Type of NAEC	MSE Value (dB) (Approx.)
1.	TMVSS-LMS and RLS algorithm based NAEC	-87.96 dB
2.	RVSS-LMS and RLS algorithm based NAEC	-80.14 dB
3.	FSS-LMS and RLS algorithm based NAEC	-73.15 dB

Table 4.4 MSE Values for Different Types of NAEC Using AR(2) Input Signal

For AR(2) input signal, it is observed from results presented in Figure 4.4.4 and also from the Table 4.4 that at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 7.82 dB better than the RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance advantage of former increases to approximately 14.81 dB in comparison to the FSS-LMS and RLS algorithm based NAEC.

From the close observation, it is also inferred that the value of MSE is quite small in case of AR(2) input as compared to both types of AR(1) signals (whether strongly correlated or weakly correlated i.e., with correlation coefficient equal to 0.9 and 0.1 respectively) and Gaussian signal as input to the presented NAEC, in all the cases. Based on the results given in Tables 4.1 – 4.4, the TMVSS-LMS and RLS algorithm based NAEC is found to be best, which has performance advantage of approximately 47.41 dB in terms of MSE, when AR(2) input signal is used in comparison to the AR(1) input signal case with  $\bar{\rho}_{c0} = 0.9$ ; this advantage increases to approximately 53.68 dB in comparison to the AR(1) input signal case with  $\bar{\rho}_{c0} = 0.1$  and this advantage further increases to approximately 70.2 dB in comparison to the Gaussian input signal case, under similar conditions.

#### Case 4.4.5:- MSE Performance of Presented NAEC Using Different Types of Input Signals

Figure 4.4.5 depicts the MSE performance and comparison of the presented nonlinear acoustic echo canceller under stationary environment, by considering different types of input signals at SNR= +17.5 dB, and then plotted the simulation results on the same graph. The different types of input signals that are considered in the Figure 4.4.5 are Gaussian signal [37], AR(1) signaling waveform with correlation coefficient  $\bar{\rho}_{c0} = 0.1$  [38], [39], AR(1) signaling waveform with correlation coefficient  $\bar{\rho}_{c0} = 0.9$  [38], [39] and AR(2) signal [30], [40], [41].

Figure 4.4.5 illustrates the MSE comparison of the presented NAEC, which is evaluated under noisy environment.

In the Figure 4.4.5,

- a) Gaussian denotes that the Gaussian signal is given as input to the presented NAEC.
- b) AR(1)-0.1 denotes that the AR(1) signal is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c0} = 0.1$ , which means that weak correlation is present between the successive samples of the signal.

- c) AR(1)-0.9 denotes that the AR(1) signal is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c_0} = 0.9$ , which means that strong correlation is present between the successive samples of the signal.
- d) AR(2) denotes that the AR(2) signal is given as input to the presented NAEC.

The equations, by which AR(1) input signaling waveform as well as AR(2) input signaling waveform have been generated, are same as used in previous cases. Also, the values of parameters for these input signals are kept same.

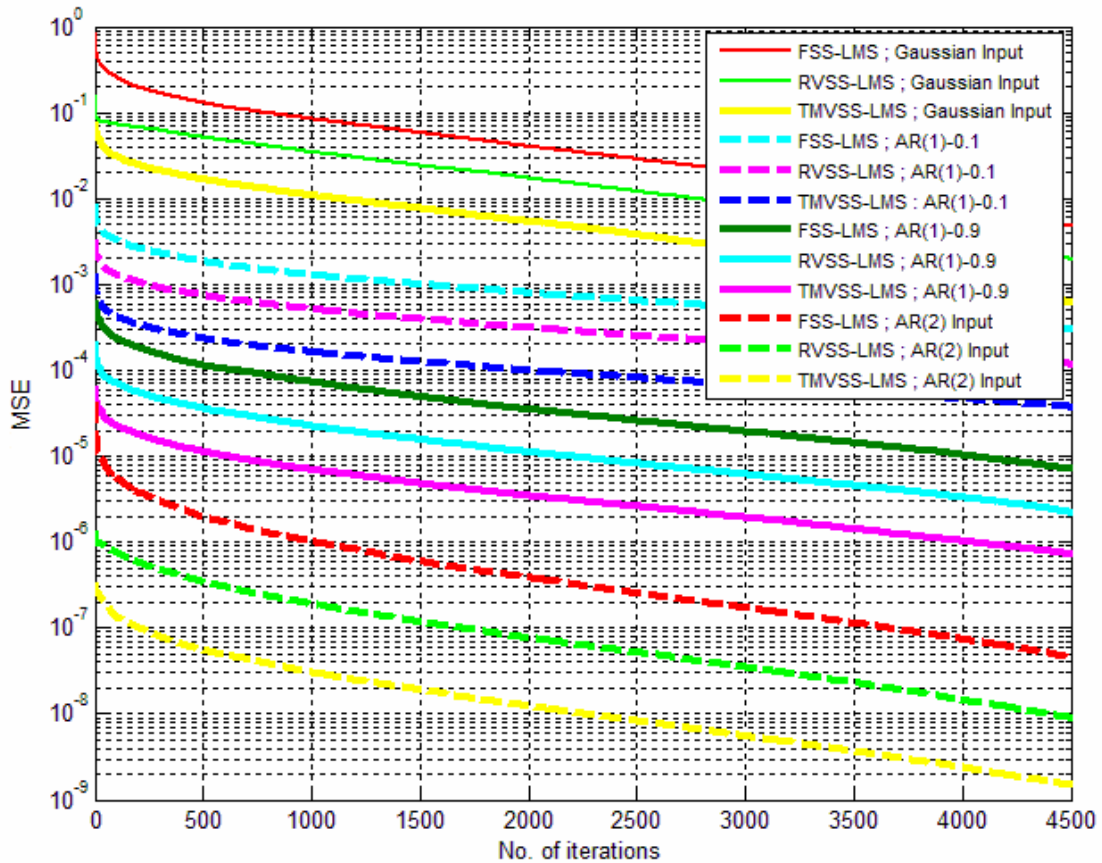


Figure 4.4.5 MSE performance of presented NAECs using different input signals (using different adaptive algorithms)

Figure 4.4.5 compares the FSS, RVSS and TMVSS algorithms for each input case, when they are used for sigmoid function parameter estimation and RLS procedure is used to update FIR filter coefficients.

At 500<sup>th</sup> iteration, for AR(2) input the MSE readings for different procedures based NAEC are given below

S.No	Type of NAEC	MSE Value (dB) (Approx.)
1.	TMVSS-LMS and RLS algorithm based NAEC	-72.50 dB
2.	RVSS-LMS and RLS algorithm based NAEC	-64.58 dB
3.	FSS-LMS and RLS algorithm based NAEC	-57.04 dB

Table 4.5 MSE Values of Different Types of NAEC Using AR(2) Input Signal

Similarly for AR(2) input signal, it is observed from results presented in Figure 4.4.5 and also from the Table 4.5 that at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 7.92 dB better than the RVSS-LMS and RLS algorithm based NAEC, in terms of MSE. However, this performance advantage of former increases to approximately 15.46 dB in comparison to the FSS-LMS and RLS algorithm based NAEC. It is apparent from the Figure 4.4.5 and Table 4.5 that both variable step-size algorithms provide much faster convergence than FSS algorithm, while maintaining the low level of misadjustment. It is inferred from the Figure 4.4.5 that the TMVSS-LMS and RLS algorithm based NAEC outperforms the RVSS-LMS and RLS algorithm based NAEC and FSS-LMS and RLS algorithm based NAEC, in terms of MSE. At iteration number 2000, the MSE readings of TMVSS-LMS and RLS algorithm based NAEC using different input signals are as

Type of Input with variance $\sigma_x^2 = 1$ and mean $m_x = 0$	MSE Value (dB) (Approx.)
AR(2)	-79.06 dB
AR(1) – 0.9	-54.63 dB
AR(1) – 0.1	-40.02 dB
Gaussian	-22.69 dB

Table 4.6 MSE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using Different Input Signals

From the Figure 4.4.5 and the Table 4.6, it is also observed that at 2000<sup>th</sup> iteration, NAEC based on TMVSS-LMS and RLS algorithm performs approximately 24.43 dB better, when AR(2) input signal is used as compared to the AR(1) input signaling waveform case with correlation parameter 0.9, in terms of MSE. This performance advantage increases to approximately 39.02 dB in comparison to the AR(1) input signaling waveform case with correlation parameter 0.1. However, this performance advantage increases to approximately 56.37 dB in comparison to the Gaussian input signal. Hence, the TMVSS-LMS and RLS algorithm based NAEC using AR(2) signal as its input showcases the lowest value of MSE. It is because of the strong correlation present between the samples of AR(2) input signal, which is weak in the case of AR(1) input signal, and even not present in the case of Gaussian input signal.

#### **4.5 MSE PERFORMANCE OF PRESENTED NAEC AT DIFFERENT NONLINEARITY LEVELS**

In this section, MSE performance comparison of the presented NAEC is performed using four different types of input signals at SNR= +17.5 dB. For each input case, three different levels of nonlinearity is considered and their MSE is calculated accordingly. From the above simulated cases, it is clear that TMVSS-LMS and RLS algorithm based NAEC outperforms the other two algorithm based NAECs, therefore only TMVSS-LMS and RLS algorithm based NAEC is used for updating the values of sigmoid parameters in further research work. For different nonlinearity levels, the values of sigmoid parameters are assumed in three different cases as  $\bar{\alpha} = \{2,4,8\}$  (which is shaping sigmoid parameter) and  $\bar{\beta} = \{3,3,3\}$  (which is clipping value parameter of sigmoid function) respectively, and then these are estimated using TMVSS adaptive algorithm for each input case independently. The presented outcomes are dependent on ensemble average of 250 independent simulation trials. Therefore, in all four different input cases, the combination of TMVSS-LMS and RLS procedures is utilized for the evaluation of MSE for presented NAEC. The design parameter values for the algorithms are kept same (as in previous section).

##### **Case 4.5.1:- MSE Performance of Presented NAEC Using Gaussian Input Signal at Different Nonlinearity Levels**

In this case, MSE performance of the presented nonlinear acoustic echo canceller is evaluated using Gaussian input signal [37]. The MSE data in the graph is plotted on the semilog scale.

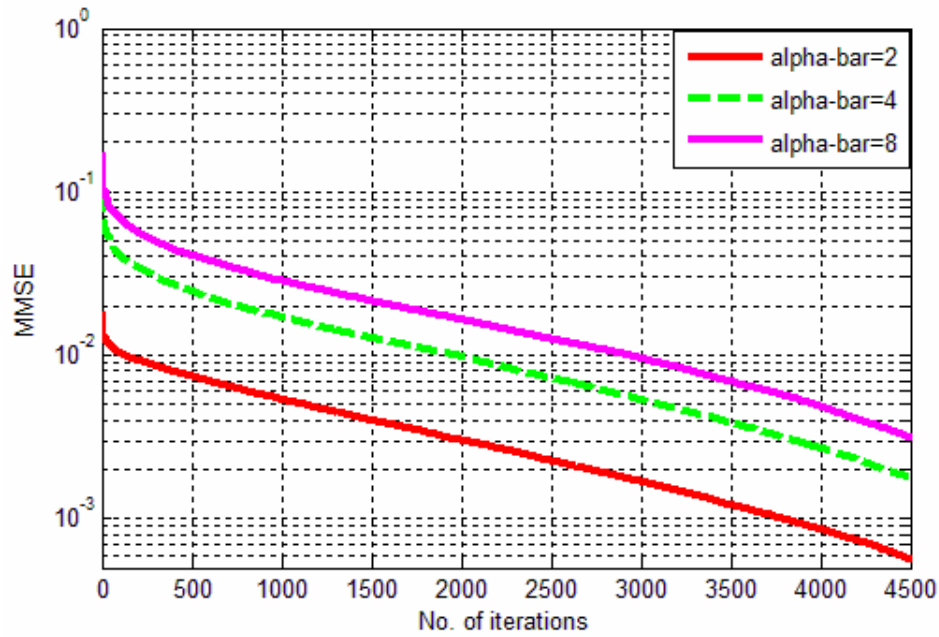


Figure 4.5.1 MSE performance of presented NAEC for Gaussian input signal at different nonlinearity levels

In the above figure, alpha-bar denotes the sigmoid parameter  $\bar{\alpha}$ . By changing the value of this sigmoid parameter, the shape of the saturation curve can be changed, and due to which nonlinearity level changes.

From results presented in Figure 4.5.1, the values of MSE at 500<sup>th</sup> iteration of TMVSS-LMS and RLS algorithm based NAEC using Gaussian input signal at the different values of alpha-bar (shape parameter of sigmoid function) are mentioned below

Values of Alpha-Bar $\bar{\alpha}$	MSE Value (dB) (Approx.)
2	-21.25 dB
4	-16.05 dB
8	-13.82 dB

Table 4.7 MSE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using Gaussian Input at Different Values of  $\bar{\alpha}$

From the Table 4.7, it is clear that for Gaussian input signal, when  $\bar{\alpha} = 2$  at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 5.2 dB better

than the case with  $\bar{\alpha} = 4$ . However, this performance advantage increases to approximately 7.4 dB in comparison to the case with  $\bar{\alpha} = 8$ , under similar conditions.

The MSE results in Figure 4.5.1 manifest that as the value of  $\bar{\alpha}$  increases, nonlinearity of saturation curve elevates; and as the value of  $\bar{\alpha}$  decreases, the nonlinearity decreases. Therefore, the value of  $\bar{\alpha}$  has direct relationship with the nonlinearity level of the saturation curve of loudspeaker. It is clear from the results that the value of MSE is least in case, when  $\bar{\alpha} = 2$  as compared to other two cases, when uncorrelated Gaussian input signal is given to the presented NAEC.

#### Case 4.5.2:- MSE Performance of Presented NAEC Using AR(1) Input Signaling Waveform with Correlation Parameter Equal to 0.1 at Different Nonlinearity Levels

In this case, MSE performance of the presented nonlinear acoustic echo canceller is evaluated under noisy environment. The MSE is evaluated using the Equation (4.27).

In this case, AR(1) signal [38], [39] with correlation coefficient  $\bar{\rho}_{c0} = 0.1$  is given as input to the presented NAEC. The AR(1) signal is obtained by using the same equation as stated in case 4.4.2; and all its parameters are also set accordingly.

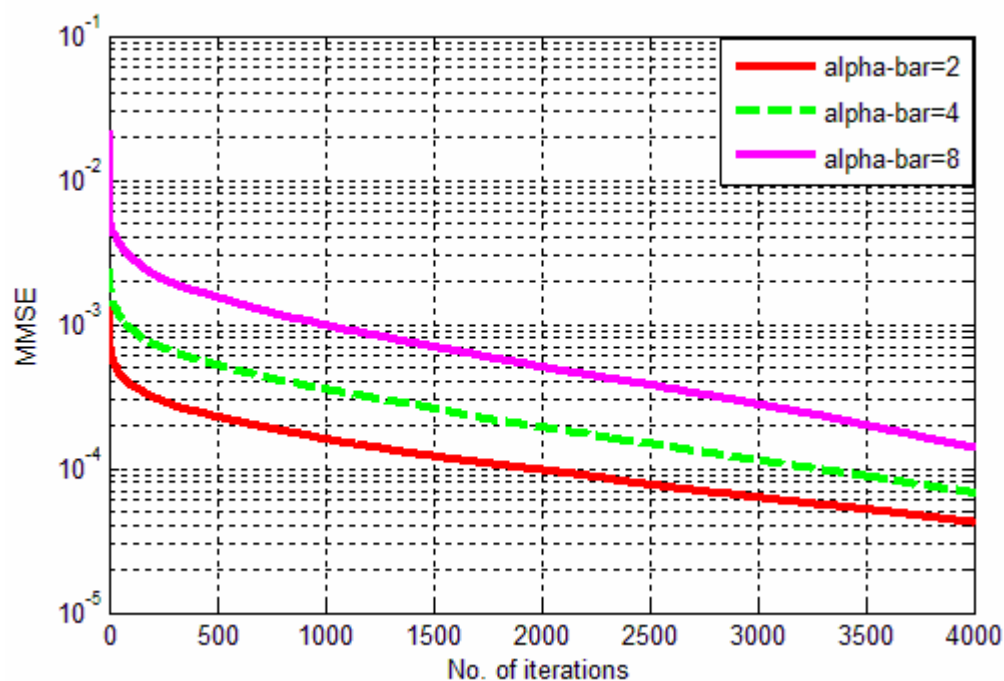


Figure 4.5.2 MSE performance of presented NAEC for AR(1) input signaling waveform (with correlation parameter  $\bar{\rho}_{c0} = 0.1$ ) at different nonlinearity levels

In the above figure, alpha-bar denotes the sigmoid parameter  $\bar{\alpha}$ . From the results presented in Figure 4.5.2, the values of MSE at 500<sup>th</sup> iteration of TMVSS-LMS and RLS algorithm based NAEC using AR(1) input signal with  $\bar{\rho}_{c0} = 0.1$  at different values of alpha-bar are provided below

Values of Alpha-Bar $\bar{\alpha}$	MSE Value (dB) (Approx.)
2	-36.41 dB
4	-32.83 dB
8	-28.09 dB

Table 4.8 MSE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using AR(1) Input with  $\bar{\rho}_{c0} = 0.1$  at Different Values of  $\bar{\alpha}$

From the Table 4.8, it is apparent that for AR(1) with  $\bar{\rho}_{c0} = 0.1$  input signal when  $\bar{\alpha} = 2$  at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 3.58 dB better than the case with  $\bar{\alpha} = 4$ . However, this performance advantage increases to approximately 8.32 dB in comparison to the case with  $\bar{\alpha} = 8$ , under similar conditions.

#### Case 4.5.3:- MSE Performance of Presented NAEC Using AR(1) Input Signaling Waveform with Correlation Parameter Equal to 0.9 at Different Nonlinearity Levels

In this case, MSE performance of the presented nonlinear acoustic echo canceller is evaluated under noisy environment. The MSE is evaluated using the Equation (4.27).

In this case, AR(1) signal [38], [39] with correlation coefficient  $\bar{\rho}_{c0} = 0.9$  is given as input to the presented NAEC. The AR(1) signal is obtained by using the same equation as stated in case 4.4.2; and all its parameters are also set accordingly. The MSE data in the graph is plotted on linear scale.

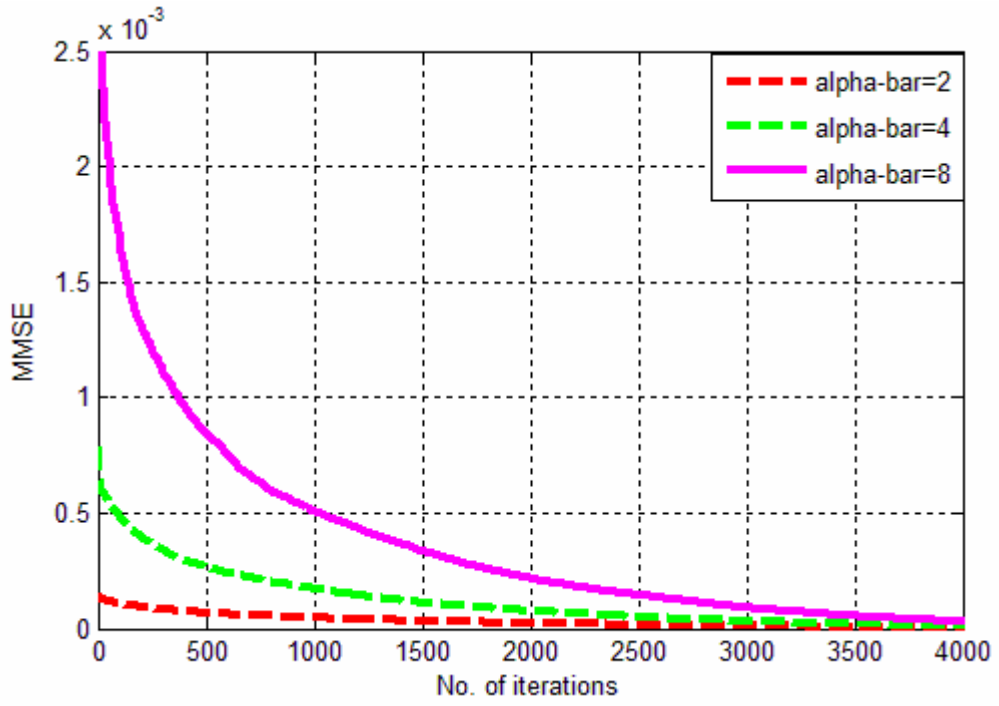


Figure 4.5.3 MSE performance of presented NAEC for AR(1) input signaling waveform (with correlation parameter  $\bar{\rho}_{c_0} = 0.9$ ) at different nonlinearity levels

In the above figure, alpha-bar denotes the sigmoid parameter  $\bar{\alpha}$ . From the results presented in Figure 4.5.3, the values of MSE at 500<sup>th</sup> iteration of TMVSS-LMS and RLS algorithm based NAEC using AR(1) input signal with  $\bar{\rho}_{c_0} = 0.9$  at different values of alpha-bar are as follows

Values of Alpha-Bar $\bar{\alpha}$	MSE Value (dB) (Approx.)
2	-41.69 dB
4	-35.68 dB
8	-30.67 dB

Table 4.9 MSE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using AR(1) Input with  $\bar{\rho}_{c_0} = 0.9$  at Different Values of  $\bar{\alpha}$

From the Table 4.9, it is inferred that for AR(1) with  $\bar{\rho}_{c_0} = 0.9$  input signal when  $\bar{\alpha} = 2$  at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately

6.01 dB better than the case with  $\bar{\alpha} = 4$ . However, this performance advantage increases to approximately 11.02 dB in comparison to the case with  $\bar{\alpha} = 8$ .

From the close observations, it is clear that the value of MSE is least in case of the AR(1) input signaling waveform with correlation parameter equal to 0.9 as compared to the AR(1) input signaling waveform with correlation parameter equal to 0.1 and the uncorrelated Gaussian input signal at  $\bar{\alpha} = 2$ . Even, when the value of sigmoid parameter is changed i.e.,  $\bar{\alpha} = [4, 8]$  then also MSE is lower in case of the AR(1) input signaling waveform with  $\bar{\rho}_{c0} = 0.9$  as compared to the AR(1) input signaling waveform with  $\bar{\rho}_{c0} = 0.1$  and the uncorrelated Gaussian input signal case.

#### Case 4.5.4:- MSE Performance of Presented NAEC Using AR(2) Input Signal at Different Nonlinearity Levels

In this section, MSE performance of the presented nonlinear acoustic echo canceller is evaluated in the presence of environmental noise.

In this case, AR(2) signal [30], [40], [41] is given as input to the presented NAEC. The AR(2) signal is obtained by using the same equation used in case 4.4.4, and its all parameters are also set as mentioned in that case.

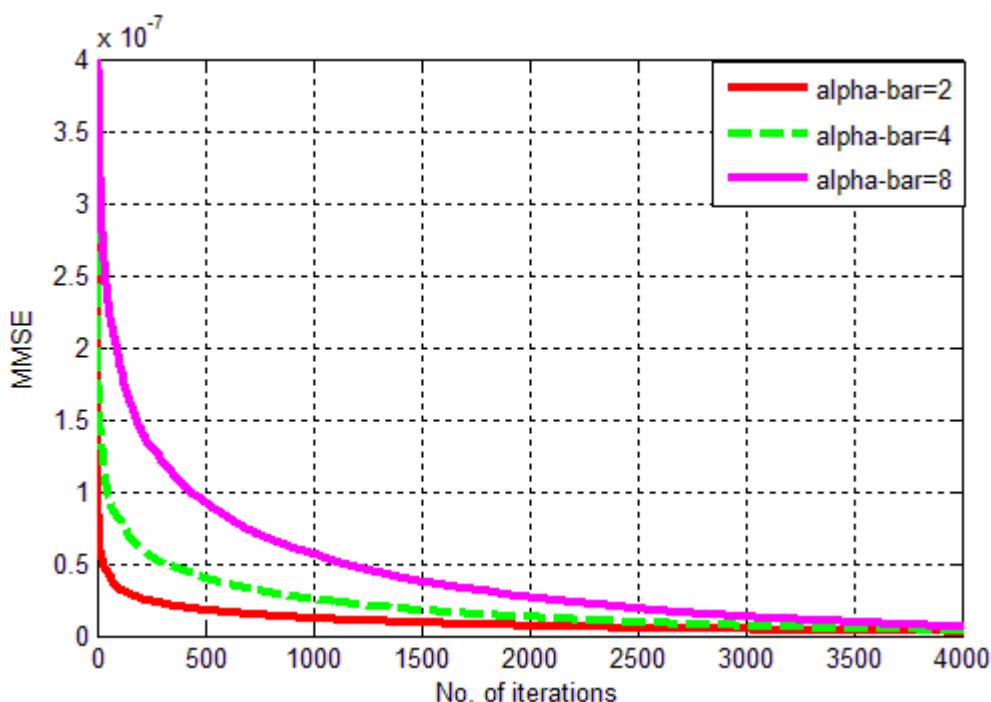


Figure 4.5.4 MSE performance of presented NAEC for AR(2) input signal at different nonlinearity levels

In the above figure, alpha-bar denotes the sigmoid parameter  $\bar{\alpha}$ . From the results presented in Figure 4.5.4, the values of MSE at 500<sup>th</sup> iteration of TMVSS-LMS and RLS algorithm

based NAEC using AR(2) input signal at different values of alpha-bar are demonstrated below

Values of Alpha-Bar $\bar{\alpha}$	MSE Value (dB) (Approx.)
2	-77.53 dB
4	-73.093 dB
8	-70.28 dB

Table 4.10 MSE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using AR(2) Input at Different Values of  $\bar{\alpha}$

From the Table 4.10, it is apparent that for AR(2) input signal when  $\bar{\alpha} = 2$  at 500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 4.437 dB better than the case with  $\bar{\alpha} = 4$ . However, this performance advantage increases to approximately 7.25 dB in comparison to the case with  $\bar{\alpha} = 8$ .

It is evident from simulation results that as value of  $\bar{\alpha}$  gets elevated, level of nonlinearity gets boosted, which in turn results in high value of MSE in all input cases. But, because of strong correlation between input samples the AR(2) input signaling waveform appears to be best choice among all. It is because of the fact that adaptive algorithms track the correlated input signal more efficiently.

#### **4.6 ERLE PERFORMANCE OF PRESENTED NAEC USING DIFFERENT INPUT SIGNALS AT DIFFERENT NONLINEARITY LEVELS**

In this case, ERLE performance of presented nonlinear acoustic echo canceller is evaluated for the different types of input signals.

In this case, we shall investigate the performance of presented NAEC using the TMVSS least-mean-square (LMS) procedure for updating parameters of nonlinear sigmoid transformation function and the RLS procedure to estimate coefficient vector of tapped-delay-line FIR filter under noisy environment. These adaptive procedures are utilized to compare the convergence characteristic of presented NAEC, and performance of the presented NAEC at different nonlinearity levels of the saturation curve of the loudspeaker is also evaluated.

For simulation, the number of samples in input signal vector is M=64 the length of  $\vec{c}(n)$  which is impulse response coefficient vector of room (indoor) (multipath in nature) is M=64.

The room (indoor) impulse response coefficients are set according to Equation (4.28), which are static in nature.

In this section, for all input cases, the shape of the nonlinear saturation curve of the loudspeaker is varied by varying the sigmoid shape parameter i.e.,  $\bar{\alpha}$  keeping the value of the clipping factor same in each case i.e.,  $\bar{\beta}$  is fixed. In this case, three different nonlinearity levels are considered by varying the value of sigmoid shape parameter. From the aforementioned simulated cases, it is apparent that the TMVSS-LMS algorithm outperforms the other two algorithms. Therefore, only the TMVSS algorithm is used for updating the values of sigmoid parameters in subsequent cases. For different nonlinearity levels, the values of sigmoid parameters are set as  $\bar{\alpha} = \{2, 4, 8\}$  and  $\bar{\beta} = \{3, 3, 3\}$  respectively, and the ERLE is evaluated for the presented NAEC using the combination of TMVSS-LMS and RLS algorithms at SNR= +20 dB.

#### Case 4.6.1:- ERLE Comparison of Presented NAEC Using Different Input Signals at Different Nonlinearity Levels

In this case, ERLE comparison of the presented NAEC is evaluated using three different input signals, and then compared with each other.

The inputs considered in this case are

- a) Gaussian signal having mean  $m_x = 0$  and variance  $\sigma_x^2 = 1$
- b) AR(1)-0.5 signal possessing mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$  and correlation coefficient  $\bar{\rho}_{c0} = 0.5$
- c) AR(2) signal exhibiting mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$

The value of the variance of noise is set equal to 0.01 i.e.,  $\sigma_\eta^2 = 0.01$ . The value of forgetting coefficient  $\lambda_r$  for RLS procedure is kept 0.97, and the value of regularizing parameter  $\delta^{-1}$  is kept 0.005 in each case.

In the Figure 4.6.1,

- a) Gaussian denotes that the Gaussian signal is given as input to the presented NAEC
- b) AR(1)-0.5 denotes that the AR(1) signal is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c0} = 0.5$
- c) AR(2) denotes that the AR(2) signal is given as input to the presented NAEC

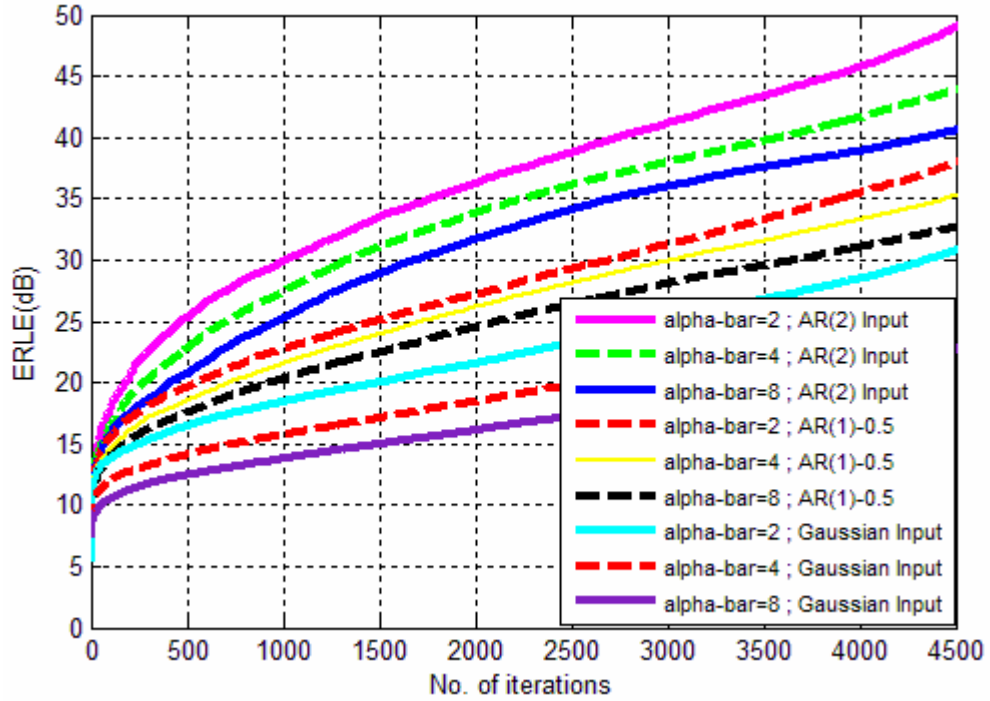


Figure 4.6.1 ERLE comparison of presented NAEC using different input signals at different nonlinearity levels

In the above figure, alpha-bar indicates the sigmoid parameter  $\bar{\alpha}$ . From the Figure 4.6.1, the values of ERLE at 3000<sup>th</sup> iteration of the TMVSS-LMS and RLS algorithm based NAEC using the Gaussian input signal, at the different values of alpha-bar are given below

Values of Alpha-Bar $\bar{\alpha}$	ERLE Value (dB) (Approx.)
2	24.91 dB
4	21.1 dB
8	18.41 dB

Table 4.11 ERLE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using Gaussian Input at Different Values of  $\bar{\alpha}$

From the Table 4.11, it is apparent that for Gaussian input signal with  $\bar{\alpha} = 2$  at 3000<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 3.81 dB better than the case with  $\bar{\alpha} = 4$ . However, this performance advantage increases to approximately 6.5 dB in comparison to the case with  $\bar{\alpha} = 8$ .

From the Figure 4.6.1, the values of ERLE at 3000<sup>th</sup> iteration of TMVSS-LMS and RLS algorithm based NAEC using the AR(2) input signal at the different values of alpha-bar are mentioned below

Values of Alpha-Bar $\bar{\alpha}$	ERLE Value (dB) (Approx.)
2	41.12 dB
4	37.96 dB
8	35.95 dB

Table 4.12 ERLE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using AR(2) Input at Different Values of  $\bar{\alpha}$

From the Table 4.12, it is inferred that for the AR(2) input signal with  $\bar{\alpha} = 2$  at 3000<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 3.16 dB better than the case with  $\bar{\alpha} = 4$ . However, this performance advantage of former increases to approximately 5.17 dB in comparison the case with  $\bar{\alpha} = 8$ .

The ERLE results in Table 4.11 and Table 4.12 manifest that as the value of  $\bar{\alpha}$  increases the ERLE performance of the presented NAEC gets degraded and as the value of  $\bar{\alpha}$  decreases its performance level improves. Therefore, the value of  $\bar{\alpha}$  has inverse relationship with the ERLE performance of the presented NAEC. It is obvious from the results that the value of ERLE is maximum in case, when the AR(2) input signal is utilized, in case  $\bar{\alpha} = 2$  is set for presented NAEC as compared to other input cases.

At iteration number 1500, the ERLE readings for the TMVSS-LMS and RLS algorithm based NAEC using the different input signals (when values of sigmoid parameters are set as  $\bar{\alpha} = 4$  and  $\bar{\beta} = 3$ ) are as follows

Types of Input	ERLE Value (dB) (Approx.)
Gaussian	17.07 dB
AR(1) – 0.5	23.9 dB
AR(2)	31.01 dB

Table 4.13 ERLE Values for the TMVSS-LMS and RLS Algorithm Based NAEC Using Different Input Signals

From the Table 4.13, it is apparent that, when  $\bar{\alpha} = 4$  in each input case, there is approximately 7.11 dB more advantage in case of the AR(2) input signal in comparison to the AR(1) input signaling waveform case with correlation parameter equal to 0.5. This performance advantage of former increases to approximately 13.94 dB as compared to the Gaussian input signal in terms of ERLE.

Case:- 4.6.2 ERLE Comparison of Presented NAEC Using AR(1) Signal with Different Correlation Coefficients at Different Nonlinearity Levels

In this case, ERLE comparison for the presented NAEC is performed using three different AR(1) signals.

The inputs considered in this case are

- a) AR(1)-0.9 signal possessing mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$  and correlation coefficient  $\bar{\rho}_{c0} = 0.9$
- b) AR(1)-0.5 signal possessing mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$  and correlation coefficient  $\bar{\rho}_{c0} = 0.5$
- c) AR(1)-0.1 signal exhibiting mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$  and correlation coefficient  $\bar{\rho}_{c0} = 0.1$

The value of forgetting coefficient  $\lambda_r$  for RLS algorithm is kept 0.97, and the value of regularizing parameter  $\delta^{-1}$  is kept 0.005 in each input case.

In the Figure 4.6.2,

- a) AR(1)-0.9 denotes that the AR(1) signal is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c0} = 0.9$
- b) AR(1)-0.5 indicates that the AR(1) signal is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c0} = 0.5$
- c) AR(1)-0.1 denotes that the AR(1) signal is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c0} = 0.1$

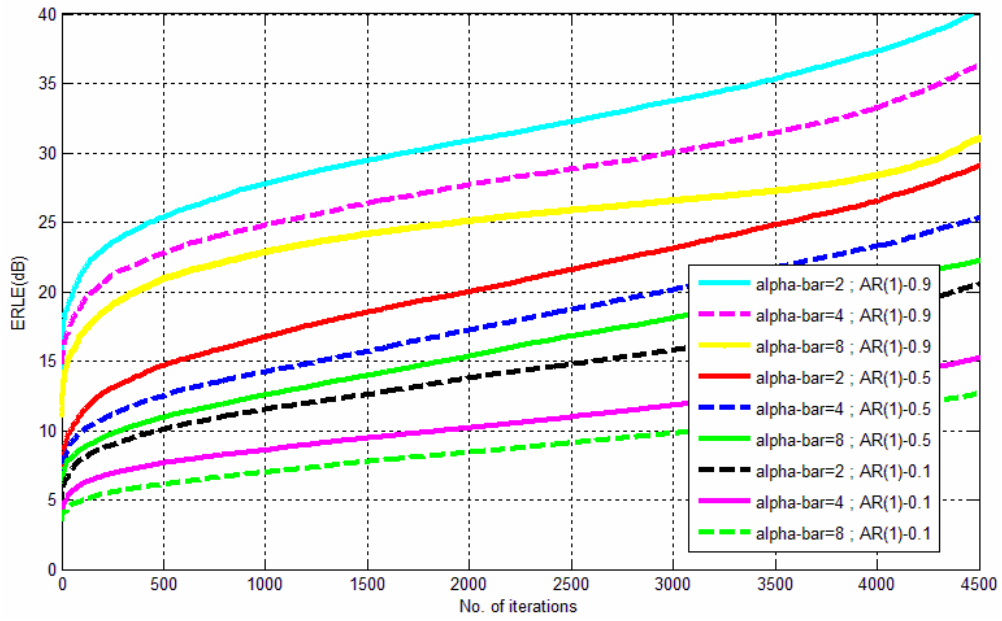


Figure 4.6.2 ERLE comparison of presented NAEC for AR(1) input signal (having different correlation coefficient) at different nonlinearity levels

In the above figure, alpha-bar indicates the sigmoid parameter  $\bar{\alpha}$ . From the Figure 4.6.2, the values of ERLE at 2500<sup>th</sup> iteration of the TMVSS-LMS and RLS algorithm based NAEC using the AR(1) input signal with different values of correlation coefficient, at  $\bar{\alpha} = 2$  are demonstrated below

Type of Input	ERLE Value (dB) (Approx.)
AR(1) – 0.9	32.22 dB
AR(1) – 0.5	21.56 dB
AR(1) – 0.1	14.74 dB

Table 4.14 ERLE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using AR(1) Input Signaling Waveform with Different Correlation Coefficients at  $\bar{\alpha} = 2$

From the Table 4.14, it is obvious that for the AR(1) input signaling waveform with correlation parameter equal to 0.9, when  $\bar{\alpha} = 2$  at 2500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 10.66 dB better than the AR(1) input signaling waveform case with correlation parameter 0.5, when value of  $\bar{\alpha} = 2$ . However, this performance advantage in former case increases to approximately 17.48 dB in comparison to AR(1) input signaling waveform case with correlation parameter 0.1, when value of  $\bar{\alpha} = 2$ .

From the Figure 4.6.2, the values of ERLE at 2500<sup>th</sup> iteration of TMVSS-LMS and RLS algorithm based NAEC using the AR(1) input signal with different values of correlation coefficient, at  $\bar{\alpha} = 8$  are given below

Type of Input	ERLE Value (dB) (Approx.)
AR(1) – 0.9	25.89 dB
AR(1) – 0.5	16.78 dB
AR(1) – 0.1	9.09 dB

Table 4.15 ERLE Values of TMVSS-LMS and RLS Algorithm Based NAEC Using AR(1) Input Signaling Waveform with Different Correlation Coefficients at  $\bar{\alpha} = 8$

From the Table 4.15, it is clear that for AR(1) input signaling waveform with correlation parameter equal to 0.9, when  $\bar{\alpha} = 8$  at 2500<sup>th</sup> iteration, the TMVSS-LMS and RLS algorithm based NAEC performs approximately 9.11 dB better than the AR(1) input signaling waveform case with correlation parameter 0.5, when value of  $\bar{\alpha} = 8$ . However, this performance advantage in former case increases to approximately 16.8 dB in comparison to the AR(1) input signaling waveform case with correlation parameter 0.1, when value of  $\bar{\alpha} = 8$ .

The ERLE results in Figure 4.6.2 as well as in aforementioned tables manifest that as the value of  $\bar{\alpha}$  increases, the ERLE performance of the presented NAEC gets deteriorated and as the value of  $\bar{\alpha}$  decreases, its performance level gets enhanced.

#### **4.7 ERLE COMPARISON OF PRESENTED NAEC USING DIFFERENT INPUT SIGNALS AT FIXED SNR VALUE**

In this case, ERLE comparison of the presented nonlinear acoustic echo canceller is carried out for different types of input signal. The ERLE is evaluated using the Equation (4.26) and the ERLE data in the graph is plotted on dB scale.

In simulation trials, the results of the TMVSS-LMS and RLS algorithm based NAEC are compared with the results of TMVSS-LMS and NLMS algorithm based NAEC, at SNR= +15 dB ( $\sigma_n^2 = 0.031623$  and  $\sigma_x^2 = 1$ ).

In this section, the shape of the nonlinear saturation curve of the loudspeaker is fixed by setting constant values of  $\bar{\alpha}$  and  $\bar{\beta}$ , which are equal to 2 and 3 respectively. In previous

section 4.6, it is observed that the nonlinearity of saturation curve of loudspeaker is lowest at  $\bar{\alpha} = 2$ . However, the TMVSS-LMS algorithm provides best results for updating the sigmoid parameter values in terms of convergence rate and misadjustment level. Therefore, only the combination of TMVSS-LMS and RLS algorithm is considered for further simulation cases regarding ERLE of presented NAEC (instead of RVSS-LMS and FSS-LMS algorithms).

The inputs considered in this section are as

- a) AR(2) signal exhibiting mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$
- b) AR(1)-0.5 signal possessing mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$  and correlation coefficient  $\bar{\rho}_{c0} = 0.5$
- c) Gaussian signal having mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$

For all the three inputs, the combination of TMVSS-LMS and RLS algorithm or TMVSS-LMS and NLMS algorithm is used, and the results are compared with each other. The value of forgetting coefficient  $\lambda_R$  for RLS algorithm is kept 0.97, and the value of regularizing parameter  $\delta^{-1}$  is kept 0.005 in each input case. The value of regularization constant  $c_N$  for NLMS algorithm is kept at 0.0019 and step-size for NLMS algorithm is set  $\mu_N = 0.15$  for each input case.

In the Figure 4.7, RLS denotes that to estimate the coefficient vector of the tapped-delay-line filter RLS procedure is used, and NLMS indicates that NLMS procedure is utilized for this purpose, and also

- a) Gaussian denotes that the Gaussian signal is given as input to the presented NAEC
- b) AR(1) indicates that the AR(1) signal is given as input to the presented NAEC with correlation coefficient  $\bar{\rho}_{c0} = 0.5$
- c) AR(2) represents that the AR(2) signal is fed as input to the presented NAEC

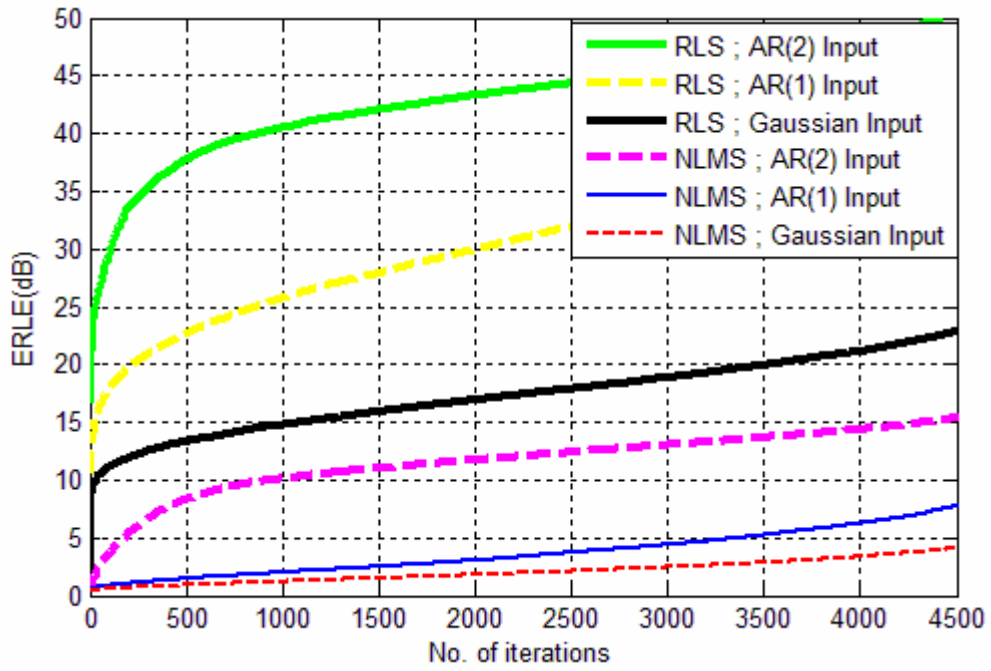


Figure 4.7 ERLE comparison for presented NAEC for different input signals at same value of SNR

At iteration number 4000, the values of ERLE for different NAECs based upon different procedures using different types of input signals are mentioned below

Types of NAEC	ERLE Value (dB) for Different Types of Input (Approx.)		
	AR(2)	AR(1) – 0.5	Gaussian
TMVSS-LMS and RLS algorithm based NAEC	48.23 dB	39.31 dB	21.14 dB
TMVSS-LMS and NLMS algorithm based NAEC	14.36 dB	6.242 dB	3.357 dB

Table 4.16 ERLE Values of Different Types of NAEC Using Different Input Signals

The ERLE results in Figure 4.7 and Table 4.16 indicate that TMVSS-LMS and RLS algorithm based NAEC gives maximum value of ERLE as compared to the TMVSS-LMS and NLMS algorithm based configuration at  $\bar{\alpha} = 2$  and  $\bar{\beta} = 3$ . This is because of higher convergence rate and low misadjustment in case of the RLS adaptive procedure as compared to the NLMS adaptive procedure. From the Figure 4.7, it is apparent that when AR(2) signal is given as input signal to presented NAEC using RLS algorithm, there is a performance advantage of approximately 33.87 dB as compared to the case of NAEC using NLMS

algorithm. It is also inferred that when AR(1) signal with  $\bar{\rho}_{c0} = 0.5$  is fed as input signal to NAEC using RLS procedure then it performs approximately 33.068 dB better than the case of NAEC using NLMS procedure. When the Gaussian input signal is given to NAEC using RLS procedure, there is performance advantage of approximately 17.783 dB in comparison to the case of NAEC using NLMS procedure. It may be concluded that TMVSS-LMS and RLS algorithm based NAEC supersedes the TMVSS-LMS and NLMS algorithm based NAEC, in terms of ERLE for any type of input signal under consideration.

#### **4.8 ERLE COMPARISON OF PRESENTED NAEC USING DIFFERENT INPUT SIGNALS AT DIFFERENT VALUES OF SNR**

In this case, ERLE comparison of the presented NAEC is performed for different types of input signals. The ERLE is evaluated using the Equation (4.26), for the TMVSS-LMS and RLS algorithm based NAEC under noisy conditions.

Simulation trials have been carried out using 10,000 iterations in each simulation run. In this section, the shape of the nonlinear saturation curve of the loudspeaker is fixed by setting the values of  $\bar{\alpha}$  and  $\bar{\beta}$  equal to 2 and 3 respectively. The presented results in Figure 4.8 are based on the average ERLE calculated in the tracking mode of operation between 9000<sup>th</sup> iteration to 10,000<sup>th</sup> iteration, for 250 independent simulation trials.

The inputs considered in this case are as

- a) AR(2) signal having mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$
- b) AR(1)-0.1 signal possessing mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$  and correlation coefficient  $\bar{\rho}_{c0} = 0.1$
- c) AR(1)-0.9 signal exhibiting mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$  and correlation coefficient  $\bar{\rho}_{c0} = 0.9$
- d) Gaussian signal with mean  $m_x = 0$ , variance  $\sigma_x^2 = 1$

The value of forgetting coefficient  $\lambda_r$  for RLS algorithm is kept 0.97, and the value of regularizing parameter  $\delta^{-1}$  is kept 0.005 in each input case. The value of SNR is varied from +5 dB to +30 dB by changing the value of  $\sigma_\eta^2$  and keeping  $\sigma_x^2 = 1$ .

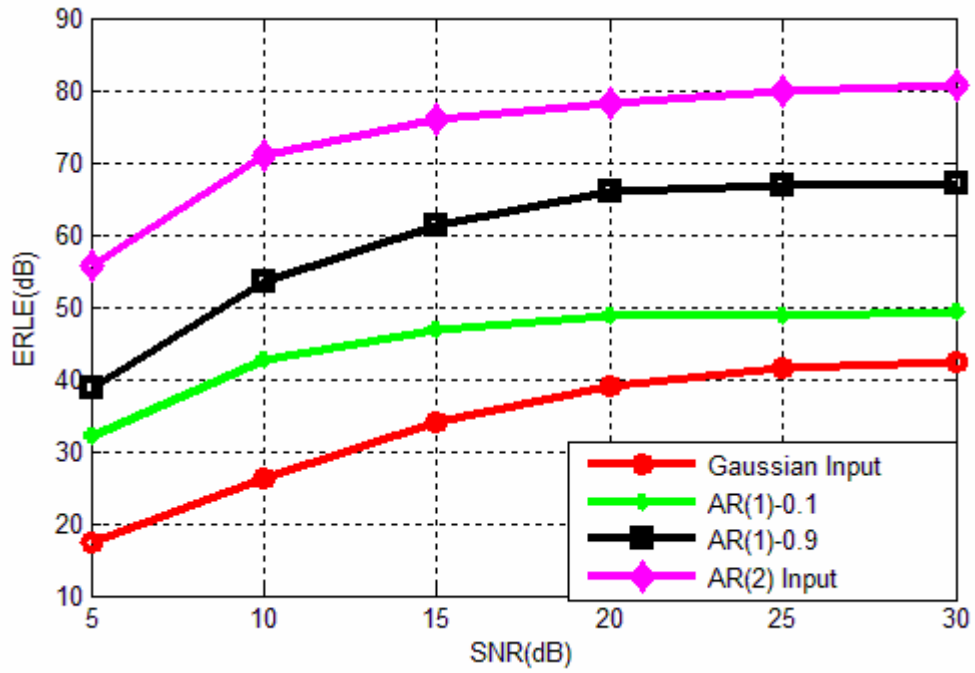


Figure 4.8 ERLE comparison of presented NAEC for different input signals at different values of SNR

The ERLE results in Figure 4.8 depict that the TMVSS-LMS and RLS algorithm based NAEC yields the highest value of ERLE for AR(2) input signal as compared to other input cases. The values of ERLE for the different SNR values and for different inputs are illustrated as follows

a) SNR= +5 dB

For this case, the value of variance of noise is set as  $\sigma_{\eta}^2 = 0.31623$

S.No	Input Considered	ERLE Value (dB) (Approx.)
1.	Gaussian	17.48 dB
2.	AR(1) with $\bar{\rho}_{co} = 0.1$	31.99 dB
3.	AR(1) with $\bar{\rho}_{co} = 0.9$	38.8 dB
4.	AR(2)	55.62 dB

Table 4.17 ERLE Values for Presented NAEC Using Different Input Signals at SNR= +5 dB

b) SNR= +10 dB

For this case, the value of variance of noise is set as  $\sigma_{\eta}^2 = 0.1$

S.No	Input Considered	ERLE Value (dB) (Approx.)
1.	Gaussian	26.36 dB
2.	AR(1) with $\bar{\rho}_{co} = 0.1$	42.52 dB
3.	AR(1) with $\bar{\rho}_{co} = 0.9$	53.55 dB
4.	AR(2)	71.06 dB

Table 4.18 ERLE Values for Presented NAEC Using Different Input Signals at SNR= +10 dB

c) SNR= +15 dB

For this case, the value of variance of noise is set as  $\sigma_{\eta}^2 = 0.031623$

S.No	Input Considered	ERLE Value (dB) (Approx.)
1.	Gaussian	33.95 dB
2.	AR(1) with $\bar{\rho}_{co} = 0.1$	46.82 dB
3.	AR(1) with $\bar{\rho}_{co} = 0.9$	61.24 dB
4.	AR(2)	75.93 dB

Table 4.19 ERLE Values for Presented NAEC Using Different Input Signals at SNR= +15 dB

d) SNR= +20 dB

For this case, the value of variance of noise is set as  $\sigma_{\eta}^2 = 0.01$

S.No	Input Considered	ERLE Value (dB) (Approx.)
1.	Gaussian	39.06 dB
2.	AR(1) with $\bar{\rho}_{co} = 0.1$	48.82 dB
3.	AR(1) with $\bar{\rho}_{co} = 0.9$	65.9 dB
4.	AR(2)	78.2 dB

Table 4.20 ERLE Values for Presented NAEC Using Different Input Signals at SNR= +20 dB

e) SNR= +25 dB

For this case, the value of variance of noise is set as  $\sigma_{\eta}^2 = 3.1623 \times 10^{-3}$

S.No	Input Considered	ERLE Value (dB) (Approx.)
1.	Gaussian	41.62 dB
2.	AR(1) with $\bar{\rho}_{co} = 0.1$	48.85 dB
3.	AR(1) with $\bar{\rho}_{co} = 0.9$	66.9 dB
4.	AR(2)	79.86 dB

Table 4.21 ERLE Values for Presented NAEC Using Different Input Signals at SNR= +25 dB

f) SNR= +30 dB

For this case, the value of variance of noise is set as  $\sigma_{\eta}^2 = 1 \times 10^{-3}$

S.No	Input Considered	ERLE Value (dB) (Approx.)
1.	Gaussian	42.33 dB
2.	AR(1) with $\bar{\rho}_{co} = 0.1$	49.3 dB
3.	AR(1) with $\bar{\rho}_{co} = 0.9$	66.99 dB
4.	AR(2)	80.62 dB

Table 4.22 ERLE Values for Presented NAEC Using Different Input Signals at SNR= +30 dB

From all the Tables 4.17 – 4.22 and Figure 4.8, it is inferred that the value of ERLE increases with the increasing value of SNR, for the presented NAEC. However, it is now obvious that the ERLE in case of AR(2) input signal is lowest among all the cases, which consequently makes the TMVSS-LMS and RLS algorithm based NAEC best choice for the audio and speech signal processing applications.

## CHAPTER 5

### CONCLUDING REMARKS AND FUTURE SCOPE

#### 5.1 CONCLUDING REMARKS

In this thesis research work, a nonlinear-acoustic-echo-cancellation (NAEC) scheme has been presented to handle the sigmoid-type nonlinearities in the presence of environmental noise. The nonlinearity level of the saturation curve of loudspeakers and/or amplifiers are varied by changing the value of the shape parameter  $\bar{\alpha}$  of sigmoid transformation function (indicating nonlinearity), while keeping the value of the clipping parameter  $\bar{\beta}$  same. The performance of presented NAEC has also been evaluated for the different types of input signals at the different nonlinearity levels. The convergence and tracking performance of FSS-LMS, RVSS-LMS and TMVSS-LMS algorithms are analyzed and compared with each other by adaptively updating the values of sigmoid parameters  $\{ \bar{\alpha} \text{ and } \bar{\beta} \}$  corresponding to a certain level of nonlinearity. Subsequently, the NLMS or RLS algorithm is utilized for the estimation of tap-coefficient vector of tapped-delay-line filter under noisy environment. The performance analysis of presented NAEC is also performed for the different input signals (uncorrelated and correlated) at the different values of SNR, which are also compared with each other at each value of SNR. The performance of presented NAEC is explored and evaluated in terms of mean-squared-error (MSE) based on the MMSE criterion and ERLE, while using the different types of input signals i.e., a) the uncorrelated input signal sequence exhibiting Gaussian characteristics and b) the correlated input signal sequence possessing the Markovian first-order process characteristics and the Markovian second-order process characteristics. The performance evaluation of presented NAEC is also conducted in the absence of environmental noise under similar conditions.

From the simulation trials with and without considering the presence of environmental noise, the following results are summarized for the updating of sigmoid parameter values  $\bar{\alpha}$  and  $\bar{\beta}$  (i.e., corresponding to the adaptive system identification using the parameter estimation) procedure.

- ✓ The FSS-LMS algorithm has lower convergence rate for both uncorrelated (i.e., Gaussian signal) and correlated (i.e., autoregressive processes of first-order and second-order) input signals.
- ✓ The FSS-LMS algorithm tracks the sigmoid parameters slowly due to its fixed step-size for all iterations; and the FSS-LMS algorithm also exhibits poor tracking capability for both types of input signals (uncorrelated and correlated).

- ✓ The FSS-LMS algorithm based NAEC fails to perform well in all input signal cases, whether the input signals is uncorrelated or correlated in nature.
- ✓ In case of the RVSS-LMS algorithm, the tracking capability of algorithm is found to be improved as compared to the FSS-LMS algorithm because in this algorithm at each iteration, the step-size is varied, and the value of step-size at each iteration increases/decreases depending upon the value of error signal at that time. From simulation results, it is inferred that the RVSS-LMS algorithm has improved tracking capability whether the input signal is uncorrelated in nature or correlated in nature.
- ✓ The RVSS-LMS procedure exhibits better convergence speed as compared to FSS-LMS procedure, but worse than the results of TMVSS-LMS algorithm for all the input signal types considered in the simulation results presented in this thesis report.
- ✓ The RVSS-LMS algorithm based NAEC possesses lower value of MSE as compared to the FSS-LMS algorithm, but it is higher than the results of TMVSS-LMS algorithm for all the input signal types (uncorrelated and correlated signals).
- ✓ The TMVSS-LMS algorithm showcases a very good tracking capability as compared to other two algorithms stated above. In this algorithm, the step-size is also varied at each iteration, and the value of step-size at each iteration increases/decreases depending upon the value of the square of a time-averaging estimate of autocorrelation of error signals i.e., at  $n^{th}$  and  $(n-1)^{th}$  instant of time. Due to this property, the TMVSS-LMS algorithm performance is independent of the uncorrelated environmental noise, while the performance of RVSS-LMS algorithm is highly dependent on the environmental noise.
- ✓ The TMVSS-LMS procedure exhibits best convergence speed as compared to other two aforementioned procedures for all the input types considered in this research work.
- ✓ The TMVSS algorithm based NAEC yields the lowest value of MSE for the uncorrelated as well as correlated input signal types.

The sigmoid parameter values ( $\bar{\alpha}$  and  $\bar{\beta}$ ) have a great impact on the nonlinearity level of the amplifier and/or loudspeaker, it means that in turn these parameters significantly influence the performance of NAEC.

- ✓ As the value of sigmoid parameter  $\bar{\alpha}$  alleviates, which is the shape parameter of nonlinear sigmoid transformation function, the nonlinearity level of loudspeakers and/or amplifiers decreases. By considering the different values of  $\bar{\alpha}$  in simulation trials, we observe that  $\bar{\alpha} = 2$  provides best results in terms of the ERLE of presented NAEC in case of the Gaussian as well as autoregressive input signals.

- ✓ By changing the value of sigmoid parameter  $\bar{\beta}$ , only clipping value of the sigmoid-type nonlinearity changes. For better convergence and proper distortion limits, the value of  $\bar{\beta}$  is fixed at 3 (as suggested in [18]) for all types of the input signals considered in this report.

From the simulation results and above mentioned points, it is inferred that the TMVSS-LMS algorithm based NAEC, in which the TMVSS-LMS algorithm is used for updating the values of the sigmoid parameters, outperforms the RVSS-LMS and FSS-LMS algorithm based NAECs for the uncorrelated as well as correlated input signals. Moreover, this algorithm shows good tracking capability, fast convergence rate and the lowest value of MSE. The value of sigmoid parameter  $\bar{\alpha} = 2$  and  $\bar{\beta} = 3$  leads to the higher value of ERLE for the presented NAEC for all input signal types considered for simulation.

From the simulation trials, the following outcomes are concluded for the estimation of tap-coefficient vector of the tapped-delay-line filter.

- ✓ For Gaussian input signal, it is observed that the RLS algorithm based NAEC outperforms the NLMS algorithm based NAEC in terms of the ERLE under the noisy environment, whether the given input is uncorrelated or correlated.
- ✓ For correlated input signals (AR(1) and AR(2)), it is inferred that the RLS algorithm based NAEC contributes the lowest MSE as compared to the NLMS algorithm based NAEC.
- ✓ The RLS algorithm based NAEC outperforms at each value of SNR for each input type considered for the simulation as compared to the NLMS algorithm based NAEC.

Nonlinear acoustic echo canceller, which utilizes a sigmoid-type transformation function to model the nonlinearity of the loudspeakers and/or amplifiers in conjunction with an FIR filter provides the lower value of the MSE when AR(2) signal is fed as input to it, the TMVSS-LMS algorithm is incorporated for updating of sigmoid parameter values, and the RLS algorithm is used for the estimation of tap-coefficient vector of underlying FIR filter. This is due to the fast tracking as well as convergence rate of the TMVSS-LMS algorithm and because of the high correlation present between the discrete samples of input signal i.e., AR(2) signal. Also, the TMVSS-LMS and RLS algorithm based NAEC demonstrates the maximum value of ERLE, among all when  $\bar{\alpha} = 2$  (means the lower side of nonlinearity level) and  $\bar{\beta} = 3$  for all the input signal types assumed for the independent simulation runs.

## 5.2 FUTURE SCOPE

Future work includes the extension of the aforementioned nonlinear acoustic echo cancellation technique by using the genetic algorithms i.e., metaheuristic optimization techniques [61], [64]. Its performance can be enhanced by replacing the TMVSS-LMS algorithm [25] by the KLMS algorithm [62] in first module of the NAEC [18] because the KLMS algorithm can handle uncertainty in the input signal more efficiently. However, the incorporation of affine-projection-algorithm (APA) [44], [63] may be an alternate approach to boost its performance. In this approach, the input vector subjected to the linear operation has been chosen in a dynamic way for updating tap-coefficient vector at higher rate. The Hammerstein system model [43] and functional-link-adaptive-filter (FLAF) model [42] can also be used in NAEC.

The presented research work may find applications in the audio and speech signal processing industries for the commercial applications, which may be extended to the nonlinear signal processing applications.

## References

- [1] Sayed M.A. and Mathews V.J. (1994). Lattice algorithms for recursive least squares adaptive second-order Volterra filtering, *IEEE Transactions on Circuits and Systems Analog and Digital Signal Processing*, 41(3), 202–214.
- [2] Panicker T.M. and Mathews V.J. (1998). Parallel-cascade realizations and approximations of truncated Volterra systems, *IEEE Transactions on Signal Processing*, 46(10), 2829–2832.
- [3] Stenger A., Trautmann L. and Rabenstein R. (1999). Nonlinear acoustic echo cancellation with 2<sup>nd</sup> order adaptive Volterra filters, *IEEE International Conference on Acoustics, Speech, Signal Processing (ICASSP)* [2<sup>nd</sup>: Phoenix, USA: 1999], pp. 877–880.
- [4] Guerin A., Faucon G. and Bouquin-Jeannes R.L. (2003). Nonlinear acoustic echo cancellation based on Volterra filters, *IEEE Transactions on Speech Audio Processing*, 11(6), 672–683.
- [5] Kuech F. and Kellermann W. (2004). Partitioned block frequency-domain adaptive second-order Volterra filter, *IEEE Transactions on Signal Processing*, 53(2), 564–575.
- [6] Kohli A.K. and Rai A. (2013). Numeric variable forgetting factor RLS algorithm for second-order Volterra filtering, *Circuits, Systems, and Signal Processing*, 32(1), 223–232.
- [7] Rai A. and Kohli A.K. (2014). Adaptive polynomial filtering using generalized variable step-size  $p^{\text{th}}$  power (LMP) algorithm, *Circuits, Systems, and Signal Processing*, 33(12), 3931–3947.
- [8] Rai A. and Kohli A.K. (2015). Volterra filtering scheme using generalized variable step-size NLMS algorithm for nonlinear acoustic echo cancellation, *Acta Acustica United With Acustica.*, 101(4), 821–828.
- [9] Fuster L. *et al.* (2015). Nonlinear filtered x-second-order adaptive Volterra filters for listening room compensation, *IEEE European Signal Processing Conference (EUSIPCO)* [23<sup>rd</sup>: Nice, France: 2015], pp. 669–673.
- [10] Nollett B.S. and Jones D.L. (1997). Nonlinear echo cancellation for handsfree speakerphones, *NSIP* [Mackinac Island, MI: 1997], pp. 1–5.
- [11] Breining C. *et al.* (1999). Acoustic echo control: An application of very-high-order adaptive filters, *IEEE Signal Processing Magazine*, 16(4), 42–69.
- [12] Stenger A. and Rabenstein R. (1999). Adaptation of acoustic echo cancellers incorporation a memoryless nonlinearity, *IEEE Workshop on Acoustic Echo and Noise Control (IWAENC)* [9<sup>th</sup>: Prcono Manor, PA, USA: 1999], pp. 1–5.
- [13] Costa J.P, Lagrange A. and Arliaud A. (2003). Acoustic echo cancellation using nonlinear cascade filters, *IEEE International Conference on Acoustics, Speech, Signal Processing (ICASSP)* [5<sup>th</sup>: Hong Kong, China: 2003], pp. 389–392.
- [14] Kuech F., Mitnacht A. and Kellermann W. (2005). Nonlinear acoustic echo cancellation using adaptive orthogonalized power filters, *IEEE International Conference on Acoustics, Speech, Signal Processing* [5<sup>th</sup>: Philadelphia, PA, USA: 2005], pp. 105–108.

- [15] Sentoni G. and Altenberg A. (2005). Nonlinear acoustic echo canceller with DABNET + FIR structure, *IEEE Workshop on Applications of Signal Processing to Audio and Acoustics* [16<sup>th</sup>: New Paltz, NY, USA: 2005], pp. 37–40.
- [16] Ahgren P. (2005). Acoustic echo cancellation and doubletalk detection using estimated loudspeaker impulse, *IEEE Transactions on Speech Audio Processing*, 13(6), 1231–1237.
- [17] Dai H. and Zhu W.P. (2006). Compensation of loudspeaker nonlinearity in acoustic echo cancellation using raised-cosine function, *IEEE Transactions on Circuits and Systems-II, Express Briefs*, 53(11), 1190–1194.
- [18] Fu J. and Zhu W.P. (2008). A nonlinear acoustic echo canceller using sigmoid transform in conjunction with RLS algorithm, *IEEE Transactions on Circuits and Systems-II, Express Briefs*, 55(10), 1056–1060.
- [19] Diniz P.S.R. *Adaptive Filtering*, 2<sup>nd</sup> ed. Norwell, MA: Kluwer, 2002.
- [20] Mathews V.J. (1991). Adaptive polynomial filters, *IEEE Signal Processing Magazine*, 8(1), 10–26.
- [21] Zhou D. *et al.* (2006). Efficient adaptive nonlinear echo cancellation using sub-band implementation of the adaptive Volterra filter, *IEEE International Conference on Acoustics, Speech, Signal Processing (ICASSP)* [5<sup>th</sup>: Toulouse, France: 2006], pp. 37–40.
- [22] Morgan D.R. (1995). Slow asymptotic convergence of LMS acoustic echo cancellers, *IEEE Transactions on Speech Audio Processing*, 3(2), 126–136.
- [23] Feuer A. and Weinstein E. (1985). Convergence analysis of LMS filters with uncorrelated Gaussian data, *IEEE Transactions on Acoustics, Speech, Signal Processing*, 33, 222–230.
- [24] Kwong R.H. and Johnston E.W. (1992). A variable step-size LMS algorithm, *IEEE Transactions on Signal Processing*, 40(7), 1633–1642.
- [25] Aboulnasr T. and Mayyas K. (1997). A robust variable step-size LMS-type algorithm: analysis and simulations, *IEEE Transactions on Signal Processing*, 45(3), 631–639.
- [26] Evans J.B., Xue P. and Liu B. (1993). Analysis and implementation of variable step-size adaptive algorithms, *IEEE Transactions on Signal Processing*, 41(2), 2517–2535.
- [27] Shetti S.S.M., Hosur S. and Gatherer A. (1997). The log-log LMS algorithm, *IEEE International Conference on Acoustics, Speech, Signal Processing (ICASSP)* [3<sup>rd</sup>: Munich, Germany: 1997], pp. 2357–2360.
- [28] Mathews V.J. and Xie Z. (1993). A stochastic gradient adaptive filter with gradient adaptive step-size, *IEEE Transactions on Signal Processing*, 41(1), 2075–2087.
- [29] Sayed A.H. and Kailath T. (1994). A state-space approach to adaptive RLS filtering, *IEEE Signal Processing Magazine*, 3(2), 18–60.
- [30] Haykin S. *Adaptive Filter Theory*, 3<sup>rd</sup> ed. Englewood Cliffs, NJ: Prentice-Hall, 1996.

- [31] Paleologu C., Ciochina S. and Benesty J. (2008). Variable step-size NLMS algorithm for under-modeling acoustic echo cancellation, *IEEE Signal Processing Letters*, 15(1), 5–8.
- [32] Kohli A.K., Rai A. and Patel M.K. (2010). Variable forgetting factor LS algorithm for polynomial channel model, *ISRN Signal Processing*, (2010), 1–4.
- [33] Kohli A.K. and Mehra D.K. (2006). Tracking of time-varying channels using two-step LMS-type adaptive algorithm, *IEEE Transactions on Signal Processing*, 54(7), 2606–2615.
- [34] Kosi K., Bito J.F. and Tar J.K. (2013). Fine tuning with sigmoid functions in robust fixed point transformation, *IEEE International Symposium on Applied Computational Intelligence and Informatics (ISACI)* [8<sup>th</sup>: Timisoara, Romania: 2013], pp. 411–416.
- [35] Shynk J.J. (1992). Frequency domain and multirate adaptive filtering, *IEEE Signal Processing Magazine*, 15–37.
- [36] Krusienski D.J. and Jenkins W.K. (2003). Adaptive filtering via particle swarm optimization, *IEEE Asilomar Conference on Signal, Systems and Computers (ACSSC)* [37<sup>th</sup>: Pacific Grove, CA, USA: 2003], pp. 571–575.
- [37] Papoulis A. *Probability, Random Variables, and Stochastic Processes*, 3<sup>rd</sup> ed. McGraw-Hill: New York, 1991.
- [38] Kohli A.K. (2011). Fading model for antenna array receiver for a ring-type cluster of scatterers, *Taylor & Francis, International Journal of Electronics*, 98(7), 933–940.
- [39] Kapoor D.S. and Kohli A.K. (2015). Simulation of basic expansion model for channel fading using AR1 process, *Wireless Personal Communications*, 85(1), 791–798.
- [40] Kuhn E.V., Kolodziej J.E. and Seara R. (2014). Stochastic modeling of the NLMS algorithm for complex Gaussian input data and nonstationary environment, *Elsevier Digital Signal Processing*, 30(1), 55–66.
- [41] Singh S. and Kohli A.K. (2013). Wireless fading paradigm for antenna array receiver for a disk-type cluster of scatterers, *Circuits, Systems, and Signal Processing*, 33(1), 1231–1244.
- [42] Comminiello D. *et al.* (2013). Functional link adaptive filters for nonlinear acoustic echo cancellation, *IEEE Transactions on Speech Audio, Speech and Language Processing*, 21(7), 1502–1512.
- [43] Vaerenbergh S.V. and Azpicueta-Ruiz L.A. (2014). Kernel-based identification of hammerstein systems for nonlinear acoustic echo cancellation, *IEEE International Conference on Acoustics, Speech, Signal Processing (ICASSP)* [Florence, Italy: 2014], pp. 3739–3743.
- [44] Lee K., Baek Y. and Park Y. (2015). Nonlinear acoustic echo cancellation using a nonlinear postprocessor with a linearly constrained affine projection algorithm, *IEEE Transactions on Circuits Systems-II, Express Briefs*, 62(9), 881–885.
- [45] Azpicueta-Ruiz L.A. (2011). Adaptive combination of volterra kernels and its

- application to nonlinear acoustic echo cancellation, *IEEE Transactions on Audio, Speech and Language Processing*, 19(1), 97–110.
- [46] Deb A., Kar A. and Chandra M. (2014). A technical review on adaptive algorithms for acoustic echo cancellation, *IEEE International Communications and Signal Processing (ICCSP)* [Melmaruvathur, India: 2014], pp. 41–45.
- [47] Shah P. *et al.* (2015). Nonlinear acoustic echo cancellation using voltage and current feedback, *IEEE Transactions on Audio, Speech and Language Processing*, 23(10), 1589–1599.
- [48] Allen J.B. and Berkley D.A. (1978). Image method for efficiently simulating small-room acoustics, *Acoustic Society of America (ASA)* [Murray Hill, New Jersey: 1978], pp. 943–950.
- [49] Elko G.W., Diethorn E. and Gansler T. (2003). Room impulse response variation due to thermal fluctuation and its impact on acoustic echo cancellation, *IEEE International Workshop on Acoustics Echo and Noise Control (IWAENC)* [11<sup>th</sup>: Kyoto, Japan: 2003], pp. 67–70.
- [50] Campbell D.R., Palomaki K.J. and Brown G.J. (2005). Room sim a MATLAB simulation of “shoebox” room acoustics for use in teaching and research, *Computer Informatics Systems*, 9(3), 48–51.
- [51] Rajesh P. *et al.* (2015). Application of adaptive filter in digital hearing aids for cancellation of noise, *IEEE International Conference on Communications and Signal Processing (ICCSP)* [Melmaruvathur, India: 2015], pp. 526–530.
- [52] Paleologu C., Benesty J. and Ciochina S. Sparse adaptive filters for echo cancellation Morgan and Claypool (eds.), *Speech and Audio Processing*. USA: Princeton, 2011.
- [53] Scarpinti M. *et al.* (2012). Nonlinear spline adaptive filtering, *Elsevier Digital Signal Processing*, 93(1), 772–783.
- [54] Widrow B. *et al.* (1976). Stationary and nonstationary learning characteristics of the LMS adaptive filter, *Proceedings of IEEE*, 64(1), 1151–1162.
- [55] Song S. *et al.* (2002). Variable forgetting factor linear least squares algorithm for frequency selective fading channel estimation, *IEEE Transactions on Vehicular Technology*, 51(3), 613–616.
- [56] García J.A., Vidal A.R.F. and Sayed A.H. (2006). Mean-square performance of a convex combination of two adaptive filters, *IEEE Transactions on Signal Processing*, 54(3), 1078–1090.
- [57] Comminiello D. *et al.* (2010). A functional link based nonlinear echo canceller exploiting sparsity, *International Workshop on Acoustics Echo and Noise Control (IWAENC)* [10<sup>th</sup>: TelAviv, Israel: 2010], pp. 1–6.
- [58] Islam S.Z. *et al.* (2009). Performance study of adaptive filtering algorithms for noise cancellation of ECG signals, *IEEE International Conference on Information, Communications, Signal Processing (ICICS)* [7<sup>th</sup>: Macau, China: 2009], pp. 1–5.
- [59] Garg H.K. and Kohli A.K. (2017). Excision of Ocular Artifacts from EEG Using

NVFF-RLS Adaptive Algorithm, *Circuits, Systems, and Signal Processing*, 36(1), 404–419.

- [60] Stenger A. and Kellermann W. (2000). Nonlinear acoustic echo cancellation with fast converging memoryless pre-processor, *IEEE International Conference on Acoustics, Speech, Signal Processing (ICASSP)* [2<sup>nd</sup>: Istanbul, Turkey: 2000], pp. 805–808.
- [61] Merabti H. and Massicotte D. (2015). Robust nonlinear acoustic echo cancellation using a metaheuristic optimization approach, *IEEE International Conference on Digital Signal Processing (DSP)* [Singapore: 2015], pp. 297–301.
- [62] Varenbergh S.V., Bes J.F. and Elvira V. (2016). On the relationship between online Gaussian process regression and kernel least mean squares algorithms, *IEEE Workshop on Machine Learning for Signal Processing (MLSP)* [26<sup>th</sup>: Salerno, Italy: 2016], pp. 1–6.
- [63] Rey H. *et al.* (2007). Variable explicit regularization in affine projection algorithm: robustness issues and optimal choice, *IEEE Transactions on Signal Processing*, 55(5), 2096–2109.
- [64] Haykin S. *Neural Networks*, 2<sup>nd</sup> ed. Pearson Education, NJ: Prentice-Hall, 1999.

## LIST OF PUBLICATIONS

- [1] Sharma J. and Kohli A.K. (2017). Nonlinear acoustic echo canceller to combat sigmoid-type nonlinearities under noisy environment, *Circuits, Systems, and Signal Processing*, under review.