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An Efficient & Less Complex Solution to Mitigate Impulsive Noise in Multi-Channel Feed-Forward ANC System with Online Secondary Path Modeling (OSPM)

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Abstract

This paper deals with impulsive noise (IN) in multichannel (MC) Active Noise Control (ANC) Systems with Online Secondary Path Modelling (OSPM) employing adaptive algorithms for the first time. It compares performance of various existing techniques belonging to varied computational complexity range and proposes four new methods, namely: FxRLS-VSSLMS, VSSLMS-VSSLMS, FxLMAT-VSSLMS and NSS MFxLMAT-VSSLMS to deal with modest to very high impulsive noise (IN). Simulation results show that these proposed methods demonstrated improved performance in terms of fast convergence speed, lowest steady state error, robustness and stability under impulsive environment in addition to modelling accuracy for stationary as well as non-stationary environment besides reducing computational complexity many folds.

1. Introduction

Periodic noise, typically the low frequency noise, is a serious issue in many noise handling applications, such as those in the industry, production plants, air conditioning units, within aerial vessels, ships, and other vehicles [1]. It also imperils human mental and physical health, particularly for the infants and the older ones [2, 3].

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Active-noise-control (ANC) is the most useful instrument for reducing this low frequency noise [4]. ANC system works on the superposition principle, which reduces the impact of undesired noise by causing destructive interference between the acoustic waves from the noise source and anti-noise signal generated by the noise controller [5]. It uses adaptive digital filters to track the noise source, acoustic atmosphere, and unknown acoustic paths [6].

An ANC system can be configured in feedforward (FF), feed backward or, combination of both, as hybrid design [6]. A single channel (SC) feedforward (FF) ANC system encompasses a reference and an error microphone, in addition to a loudspeaker known as secondary source, as depicted in Figure 1. The reference and error microphones are used to pick-up undesired $x_r(n)$ and residual $e(n)$ noises, respectively. With the help of these two signals, an anti-noise signal $y(n)$ with the same amplitude as of undesired noise signal but opposite in phase is generated by the noise control adaptive filter called control filter represented by $W(n)$) and released through secondary source (loudspeaker). The cancelling signal $y(n)$ propagates through secondary path $S(n)$ to the error microphone where residual error $e(n)$ is calculated which is iteratively used to update control filter's $W(n)$ coefficients [7].

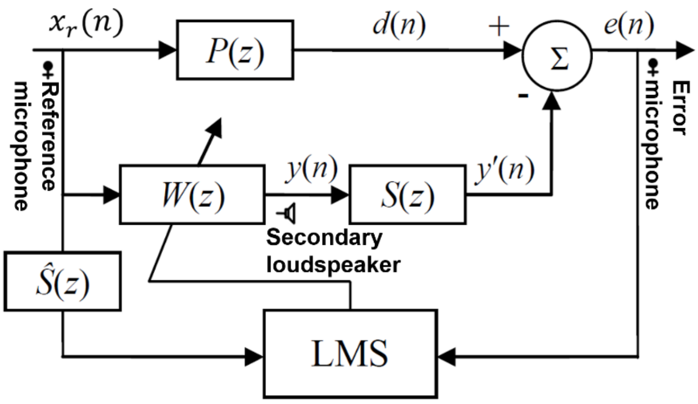

Figure 1: Single-channel (SC) feedforward (FF) ANC system.

In an ANC system, coefficients of control filters are updated recursively on each iteration using adaptive algorithm [4, 5]. Least Mean Square (LMS) algorithm and its different variants have proven most effective adaptive algorithms in ANC systems due to its simplicity and performance [8]. Filtered-x-Least Mean Square (FxLMS) is a renowned, simplest and commonly used adaptation algorithm for ANC systems [8, 9]. The input reference signal $x_r(n)$ in the FXLMS algorithm is passed through a prototype of the perceived secondary acoustic path $\hat{S}(n)$, succeeding adaptive noise controller $W(n)$, and therefore termed as "filtered x algorithm". Although, FxLMS algorithm is moderately resilient to inaccuracies between secondary path $S(z)$ and modeling filter $\hat{S}(z)$;however, the noise reduction capabilities are lower than to what are under ideal environment [9]. Thus, to cater for varying nature of secondary path and its effect on the overall performance of an ANC system, online identification or modeling of secondary path is essential to preserve stability, and robustness and to keep noise reduction performance at optimum level [10]. Eriksson and Allie [11] proposed a method to approximate the secondary path coefficients by infusing an internally generated auxiliary random white noise $v_w(n)$ into the system as shown in Figure 2. Modeled secondary path $\hat{S}(z)$ is estimated by measuring response of original secondary path $S(z)$ to this auxiliary white noise $v_w(n)$. Figure 2 shows the use of an extra online secondary path modelling (OSPM) adaptive filter $\hat{S}(z)$, based on LMS algorithm, in addition to the FxLMS algorithm-based control filter $W(z)$. The reference noise signal $x_r(n)$ propagates through primary path $P(z)$, (between input noise source and error microphone) while cancelling signal propagates through secondary path $S(z)$, (from secondary source (loudspeaker) towards error microphone) where residual error $e(n)$ is calculated to update control filter $W(z)$.

A glaring issue that Eriksson's method faces is that auxiliary random white noise $v_w(n)$ turns up in the residual error signal $e(n)$ which interferes with convergence of control filter $W(z)$. Similarly, the residual error $e(n)$ itself causes hindrance to the modelling process and convergence of OSPM filter. Various researchers proposed different methods for improvement in Eriksson's technique. For example, Akhtar and colleaguesproposed improvement in Eriksson's method by using a simple VSSLMS algorithm for modelling process [12]. Ahmed and colleagues [13] proposed betterment through two stage Auxiliary Noise Power scheduling (ANPS) to calculate time varying gain $G(n)$.. Yang and colleagues [14] innovated use of self-tuning power scheduling for determining the gain $G(n)$ based on the variations of the modeling error $g\ (n)$ whereas three adaptive filters are used to tune the step size μ_s of OSPM filter. Additionally, to speed up the process of reducing disturbances in the modelling process, an additional reference signal cancelling filter $H(z)$ was also utilized in [14].

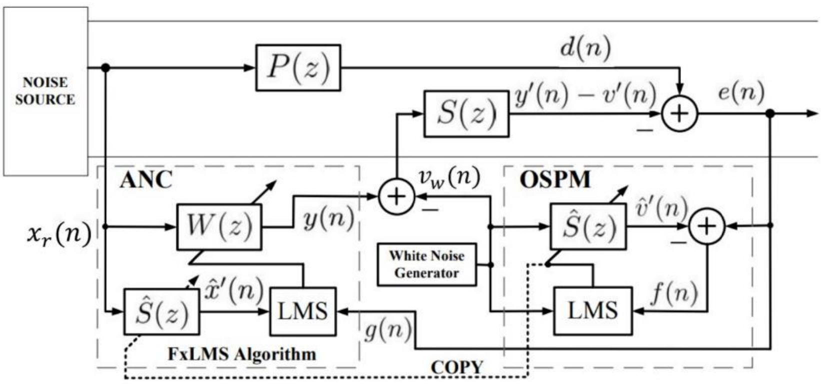

Figure 2: Online Secondary Path Modeling (OSPM) by Eriksson.

A single-channel ANC system (as shown in Figure 1 & Figure 2) is an effective tool to manage low frequency noise in a narrow duct. However, in more practical scenarios, as the noise field grows in an extended channel or in any large enclosure, the process of noise control or cancellation becomes further intricate than in a simple narrow channel.

Therefore, in order to manage such comprehensive and complicated noise scenarios, it becomes imperative to deploy a multichannel ANC (MCANC) system made up of several secondary sources, numerous error sensors, and different reference mics [15]. In Figure 3, a $(I \times J \times K)$ MCANC structure with I number of reference noise inputs $x_{r_i}(n),\ for\ i = 1, 2, 3, \ldots\ldots, I$, J number of secondary loudspeakers, and K number of error microphones

$e_k(n),\ for\ k = 1, 2, 3, \ldots\ldots, K$, is shown. In such a construction of MCANC system, a total of $J \times K$ time varying secondary paths $S_{kj}(n)$ are required to be modelled through OSPM process which is comparatively a more cumbersome job than for a single channel ANC system. This increase in complexity is mainly due to generation of complicated error signal $e_k(n)$ from each of k error microphones which is a combination of signals arriving from different primary $P_{ki}(n)$ and secondary $S_{kj}(n)$ paths. S.M. Kuo and D.R. Morgan concluded in [4] that different reference signals $x_{r_i}(n)$ may be averaged over to make single reference signal $x_r(n)$ which will have same effect as each of the individual reference signals combined but with reduced complexity. Thus, a general $1 \times J \times K$ MCANC system will be considered in this paper.

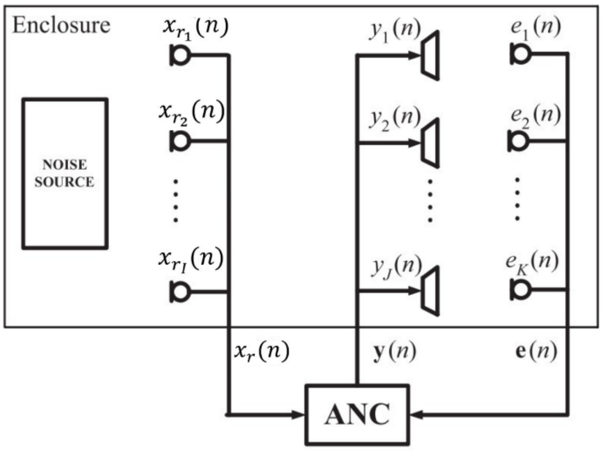

Figure 3: Structure of I × J × K MC ANC system.

Most researchers, including [12, 13, 14, 16], primarily dealt with Gaussian noise, however, many practical applications in industry and construction like stamping and cutting machinery in the production set-ups, pile drivers and gasoline engines etc. require dealing with impulsive noise (IN) [17, 18].

IN is often characterized by strong, abrupt mutations that change the signal's distribution into a non-Gaussian one [19]. A symmetric α-stable distribution can be used to model impulsive noise with the following characteristic function [17]:

$$f(x) = e^{-\gamma|x|^{\alpha}} \#(1)$$

Where α in above equation is the characteristic exponent that determines form of a distribution and its value ranges from $0 < \alpha < 2$. Tail will be heavier for α closer to 0, depicting very high impulsive nature of the noise. On the other end, as α approaches 2, the impulsive nature keeps on diminishing and distribution becomes more and more Gaussian. γ, in (1) is the scaling parameter which if set to 1, makes the $S\alpha S$ distribution a standard distribution. Same will be utilized in this paper i.e., $0 < \alpha < 2$ and $\gamma = 1$. Figure 4 shows a standard $S\alpha S$ distribution for different values of α.

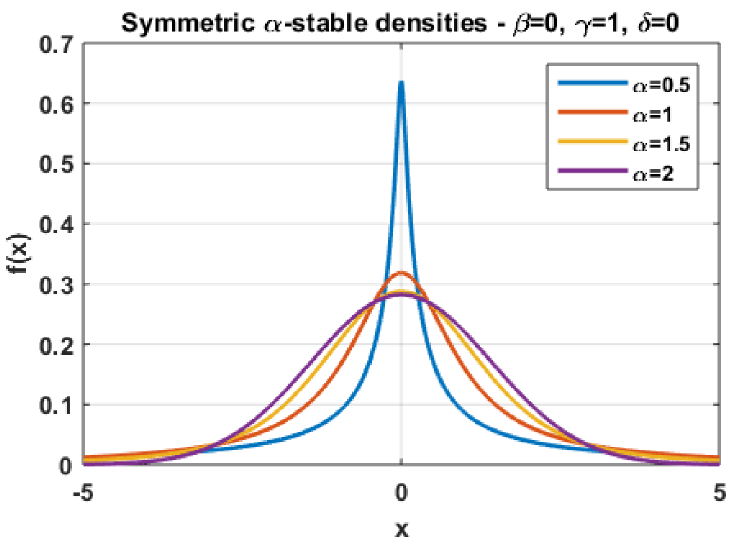

Figure 4: PDFs for standard SαS distribution of various α.

The traditional FxLMS algorithm, which minimizes error signal's variance, has shown to be quite effective at suppressing Gaussian noise [8]. However, due to non-existence of second-order moment in impulsive noise, the FxLMS method degrades and diverges when dealing with IN [20]. Filtered-x least mean p-power (FxLMP) approach as described by Leahy [21] works on minimizing the lower order fractional moment of error, p ($0<p<\alpha$), which occurs for stable distributions. In terms of active IN suppression, it is more resilient than the FxLMS algorithm. Its convergence speed, however, is very slow, particularly when noise becomes increasingly impulsive. Furthermore, it necessitates a difficult process of prior approximation of p based on α for adequate results. Sun [22] and Akhtar [23] proposed modifications in FxLMS by applying threshold in the algorithm. This threshold eliminate the aberrant values in reference noise and / or error signal/s, which may lead to instability in the ANC system. Sun used Modified Reference FxLMS (MRFxLMS) algorithm [22] to discard any value of reference signal above a certain threshold while Akhtar presented Threshold based FxLMS (Th-FxLMS) algorithm [23] to clip samples of reference noise and / or error signal/s above threshold to provide stability in the system. Similarly, Zeb [24], in 2017, employed same threshold concept using Filtered-x Recursive Least Squares (FxRLS) algorithm and suggested Threshold based FxRLS (TFxRLS) algorithm for IN in ANC systems. The TFxRLS algorithm improved the convergence of the system greatly but conceded on increased computational complexity. Zeb [24] also proposed hybrid Modified Gain FxRLS-Normalized Step Size FxLMS (MGFxRLS - NSSFxLMS) algorithm that shows faster convergence speed than NSSFxLMS with lesser complexity than FxRLS. Researchers, in [22, 23, 24], worked with offline modelling in their threshold-based algorithms as computation of optimal threshold was not possible in the case of ANC systems with OSPM. Jabeen and colleagues [16] employed OSPM for IN in single channel ANC system using FxRLS with the help of an additional filter as in Yang's method [14] and proposed three different variants namely, FxRLS-FxRLS, MGFxRLS-FxRLS and VSSFxNLMS-FxRLS. These variants improved modeling accuracy, provided faster convergence and robustness with varying computational complexities. Although, FxRLS and its variants [16, 24] improved performance, but its complexity is of order $O(n^2)$ as compared to the order $O(n)$ complexity of the algorithms belonging to FxLMS family.

Another technique to deal with IN, but still keeping the complexity low, is to use high-order-error-power (HOEP) adaptive algorithms [25, 26, 27]. Filtered-x Least Mean Absolute Third (FxLMAT) algorithm is one such HOEP algorithm that uses mean absolute third power of error signal $e(n)$ and outperforms FxLMS for majority of noise probability densities [26, 27, 28]. However, FxLMAT faces stability issues because of its dependence on various input characteristics i.e., weight initialization and variance etc. [28]. Xiong, in [29], formulated normalized LMAT (NLMAT) to cater for these instability issues which can subdue non-Gaussian noise better than other algorithms. Moroever, H. A. Khan and colleagues [30], employed FxLMAT to mitigate IN in single channel ANC System with OSPM. Khan proposed different variants, FxLMAT, MFxLMAT and VSSFxRNLMAT [30] to be used in control filter $W(n)$ while employing VSSLMS in modeling filter $\hat{S}(n)$ in addition to a third filter $H(n)$ as in yang's method [14].

Various researchers [22, 24, 20, 23] presented different methods to alleviate IN but almost all of them worked with offline modeling of secondary path which are not reliable solutions for time varying paths. Recently, Jabeen and colleagues [16] and Hashir and colleagues [30] worked on Single channel ANC system with OSPM for IN.

However, there is still no published research that can control the IN actively and adaptively in a MC ANC systems along with the employment of OSPM technique. Considering this fact, we took motivation to undertake

The layout of remaining paper is that Section-II briefly discuss Akhtar's method for MCANC system with OSPM. Section-III presents new proposed techniques, followed by section-IV which comprises of complexity comparisons of various methods discussed in this paper. Section-V shows computer simulations to validate results of proposed methods, summed up by concluding note.

2. Section-II: Basic MC ANC System with OSPM

Akhtar and colleagues [12] presented an efficient VSS-LMS algorithm based MC ANC system for Gaussian input using Eriksson's [11] structure of OSPM to keep the complexity low (Figure 5). This variable step size (VSS) strategy used power ratio $\rho_k(n)$ of error signals $e_k(n)$ and $f_k(n)$ to compute step size $\mu_{s_k}(n)$ for OSPM filters as follows:

$$\mu_{s_k}(n) = \rho_k(n)\mu_{s_{min}} + \left(1 - \rho_k(n)\right)\mu_{s_{max}} \#(2)$$

Where $\mu_{s_{min}}$ and $\mu_{s_{max}}$ are lower and upper step size values, determined experimentally. Power ratio $\rho_k(n)$ is given by:

$$\rho_k(n) = \frac{P_{f_k}(n)}{P_{e_k}(n)} \#(3)$$

These powers $P_\gamma(n)$ are estimated through low pass estimator (LPE), as: -

$$P_\gamma(n) = \lambda P_\gamma(n-1) + (1-\lambda)\gamma^2(n) \quad ; \quad \gamma = f, e \#(4)$$

Whereas error signals are defined as: -

$$e_k\,(n) = \; d_k\,(n) - \left[y'_{k1}(n) + y'_{k2}(n)\right] - \left[v'_{k1}(n) + v'_{k1}(n)\right] \quad ; \quad d(n) = p_{k1} * x_r(n)\#(5)$$

and

$$f_k\,(n) \; = \; e_k\,(n) - [\hat{v}'_{k1}(n) + \hat{v}'_{k1}(n)]\#(6)$$

Akhtar and colleagues initialized OSPM filters by offline modeling which was stopped when error was lowered to -5 dB. Afterwards, OSPM filters are updated using following: -

$$\hat{s}_{kj}\,(n+1) = \; \hat{s}_{kj}\,(n) + \; \mu_{s_k}(n)\left[f_k(n) \;\; v_j(n)\right]\#(7)$$

After convergence of OSPM filters, Control filters in Akhtar's method are updated by MeFxLMS algorithm as: -

$$w_j\,(n+1) = \; w_j\,(n) + \; \mu_{w_j}\left[f_1(n)\,\hat{x}'_{j1}(n) \; + \; f_2(n)\,\hat{x}'_{j2}(n)\right]\#(8)$$

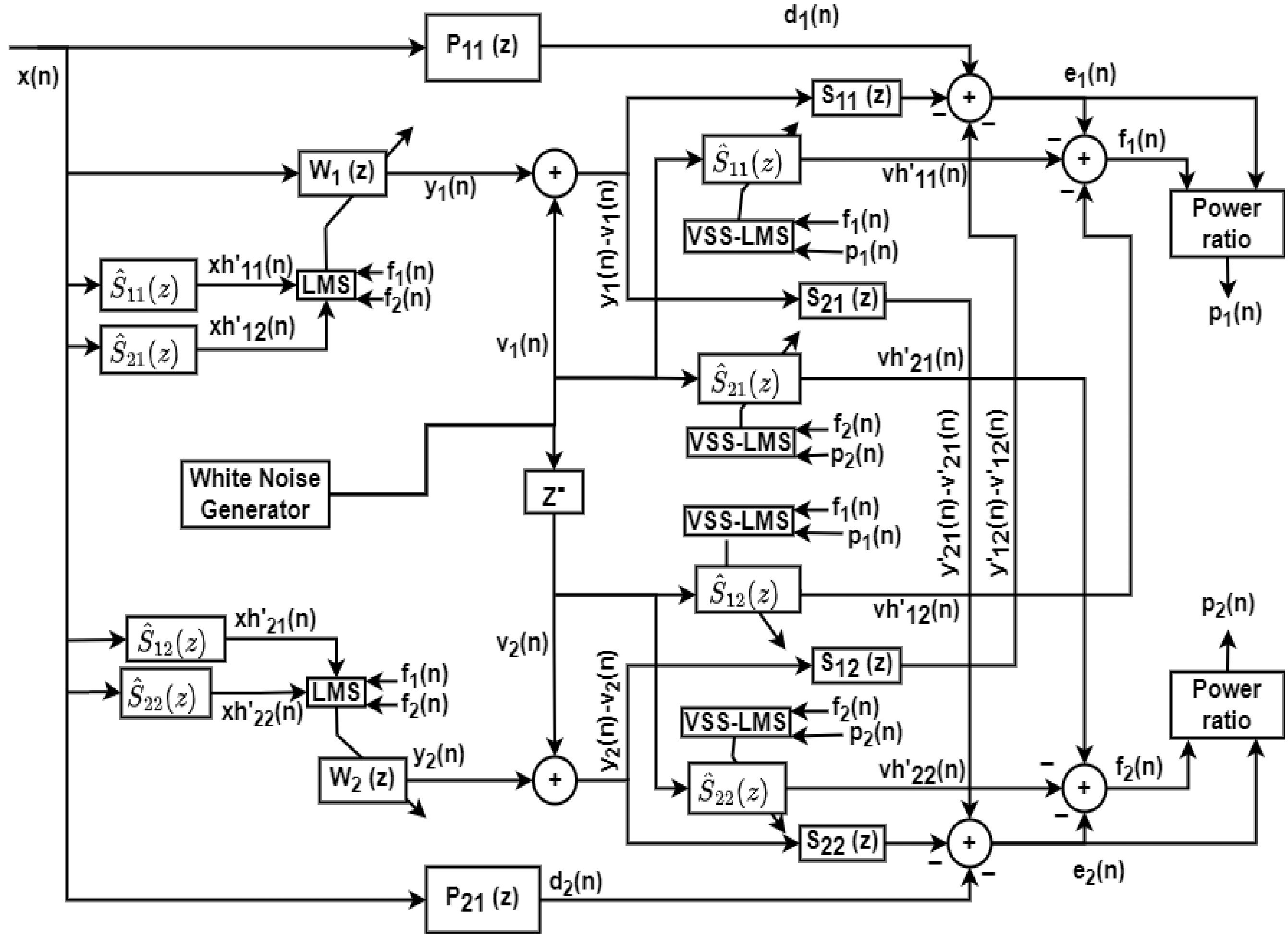

Figure 5: Akhtar's method for OSPM in MC 1x2x2 ANC System.

3. Section-III: Proposed Methods

A. *Proposed Method – 1: FxRLS & VSSLMS*

FxRLS algorithm has been proven favorable in dealing with impulsive noise in single channel ANC system [16, 24]. In this method (Figure 6), FxRLS has been employed in control filters of MC ANC system while modelling filters are adapted through VSSLMS algorithm as follows: -

$$\hat{s}_{kj}\ (n+1) = \ \hat{s}_{kj}\ (n) + \ \mu_{s_k}(n)\ \left[f_k(n)\ \ v_j(n)\right] \#(9)$$

where $f_k(n)$ is modelling error signal, defined as: -

$$f_k(n) = \ \ e_k\ (n) - [\hat{v}'_{k1}(n) + \hat{v}'_{k1}(n)] \#(10)$$

and

$$e_k\ (n) = \ d_k\ (n) - \left[y'_{k1}(n) + y'_{k2}(n)\right] - [v'_{k1}(n) + v'_{k1}(n)]\ \#(11)$$

$$d_k(n) = p_{k1} * x_r(n)$$

while step size $\mu_{s_k}$is calculated through: -

$$\mu_{s_k}(n) = \ \rho_k(n)\mu_{s_{min}} + \left(1 - \rho_k(n)\right)\mu_{s_{max}}\ \#(12)$$

$\mu_{s_{min}}$ and $\mu_{s_{max}}$ are lower and upper step size values determined experimentally and $\rho_k(n)$ is power ratio of modelling and residual errors, given as: -

$$\rho_k(n) = \ \frac{P_{f_k}(n)}{P_{e_k}(n)}\ \#\ (13)$$

where $P_{f_k}(n)$ and $P_{e_k}(n)$ are powers of $f_k(n)$ and $e_k(n)$ error signals which are estimated employing low pass estimator of the form:

$$P_{\gamma_k}(n) = \lambda P_{\gamma_k}(n-1) + (1-\lambda)\gamma_k{}^2(n)\ \ ;\ \ \ \gamma = f, e\ \#(14)$$

After convergence of OSPM filters, FxRLS algorithm is used to update ANC filters as following: -

$$w_j\ (n+1) = \ w_j\ (n) + \ f_1(n)\ K_{w_{j1}}(n) + f_2(n)\ K_{w_{j2}}(n) \#(15)$$

where

$$K_{w_{kj}}(n) = \ \frac{P_{w_{kj}}\hat{x}'_{kj}(n)}{\hat{x}'^T{}_{kj}(n)\ \ P_{w_{kj}}\ \hat{x}'_{kj}(n) + \lambda}\ \ ;\ \ \#(16)$$

$P_{w_{kj}}$ is initialized as $P_{w_{kj}}(0) = \delta^{-1} I$ and δ is regularization parameter having experimentally determined value.

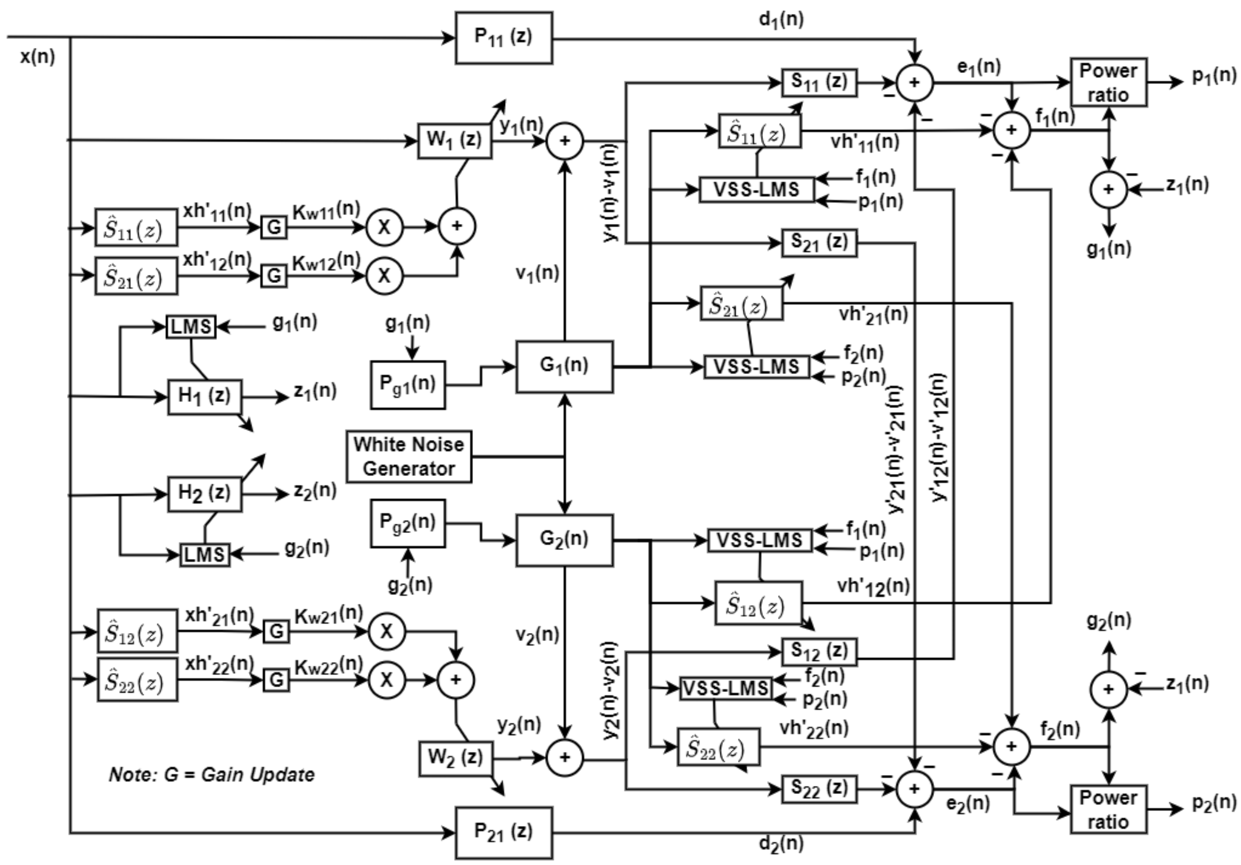

Figure 6: Proposed method – 1, FxRLS & VSSLMS.

B. *Proposed Method – 2: VSSLMS & VSSLMS*

Proposed method - 1, FxRLS & VSSLMS, produced good results but at the cost of high computational complexity. Consequently, there was a dire need to find a less complex solution to handle impulsive noise. In this method, a less complex algorithm, VSSLMS, is used in both modeling and control filters that yet shows performance comparable to that of FxRLS variant discussed above. Modeling process is same as given in Proposed method 1 (equations 9-14). Thus, following equations are used to update OSPM filters: -

$$\hat{s}_{kj}\,(n+1) = \hat{s}_{kj}\,(n) + \mu_{s_k}(n)\,[f_k(n)\;\; v_j(n)] \#(17)$$

Whereas control filter is updated using: -

$$w_j\,(n+1) = w_j\,(n) + \mu_{w_j}(n)\,[f_1(n)\,\hat{x}'_{j1}(n) + f_2(n)\,\hat{x}'_{j2}(n)] \#(18)$$

Step size $\mu_{w_j}(n)$ to be computed as under: -

$$\mu_{w_k}(n) = \rho_k(n)\mu_{w_{min}} + (1-\rho_k(n))\mu_{w_{max}} \#(19)$$

And $\rho_k(n)$ is calculated using (13) and (14)

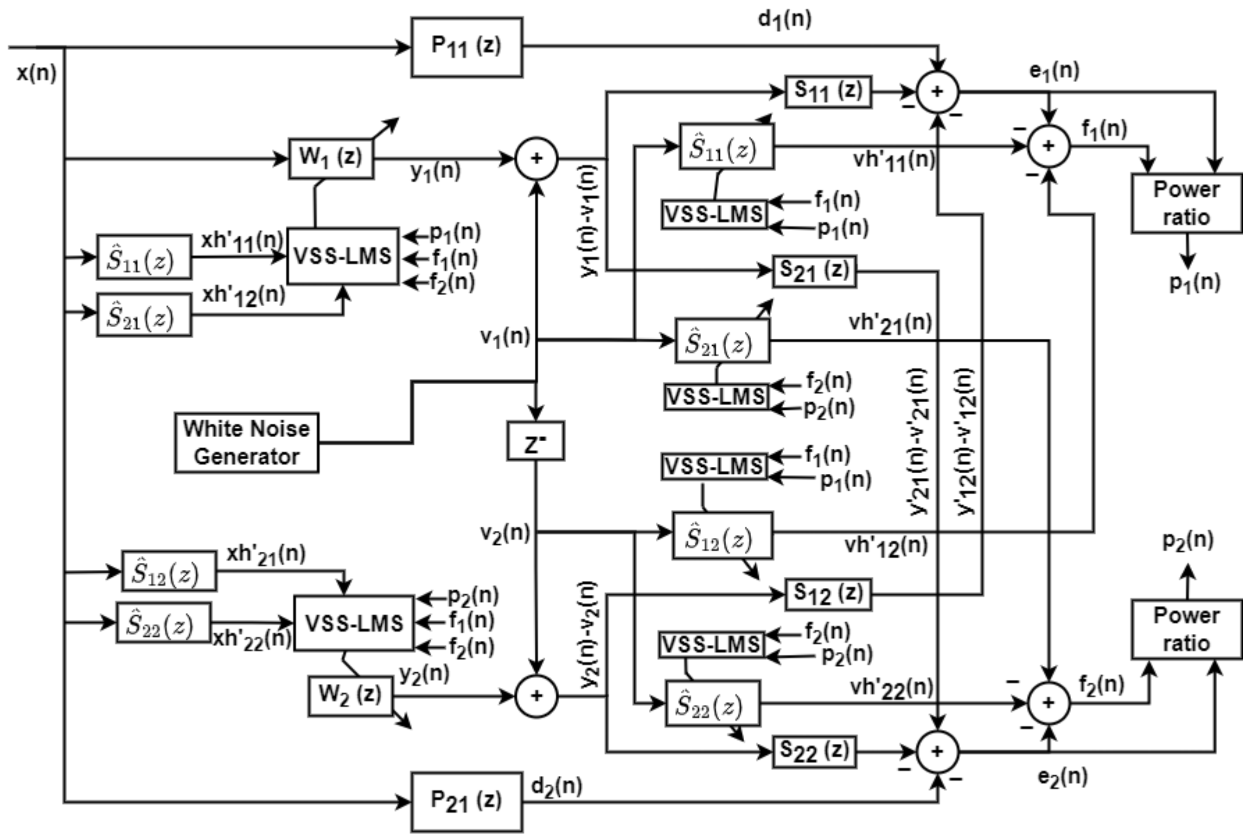

Figure 7: Proposed method – 2, VSSLMS & VSSLMS.

C. Proposed Method – 3: FxLMAT & VSSLMS

Proposed Method - 2 provided simplicity, but convergence speed was affected. To find fast convergence along with less complexity, a HOEP algorithm, FxLMAT in combination with VSSLMS (Figure 8) is tried as under:

Control filters will be adapted using: -

$$w_j(n+1) = w_j(n) + \mu_w(n)\left[f_1^{\,2}(n)sign\big(f_1(n)\big)\hat{x}_{j1}(n) + f_2^{\,2}(n)sign\big(f_2(n)\big)\hat{x}_{j2}(n)\right]\#(20)$$

where $\mu_w(n)$ is determined experimentally.

Modelling filters are adapted through VSSLMS algorithm using equations 9-14

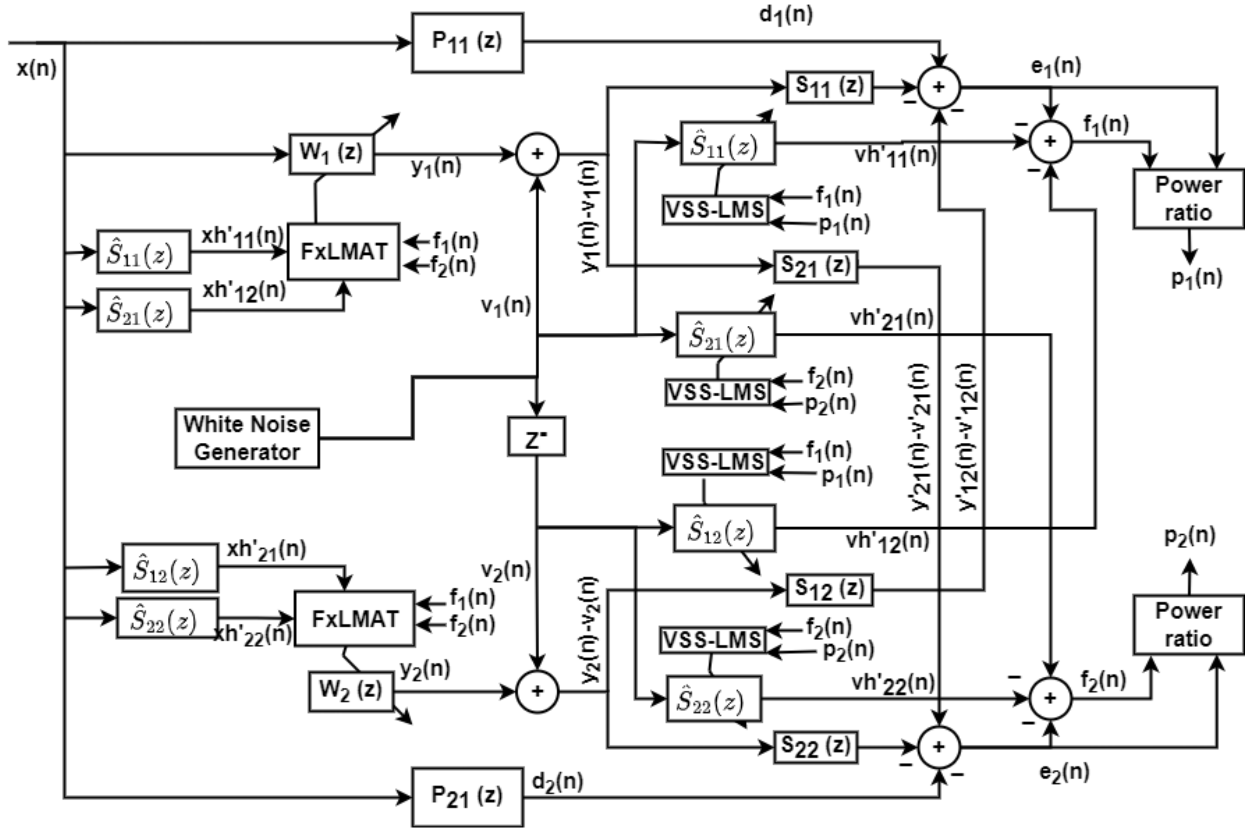

Figure 8: Proposed method – 3, FxLMAT & VSSLMS.

D. Proposed Method – 4: NSS MFxLMAT & VSSLMS

Bona fide FxLMAT did not produced anticipated results. A modified version of FxLMAT is proposed here which has much less computational intricacy but shows performance comparable to that of FxRLS variant discussed above.

Here, again, the modelling process is carried out using VSSLMS technique similar as given in Proposed method 1 (equations 9-14). Therefore, details of only control filters will be discussed here. Below is the weight update equation for control filters: -

$$w_j(n+1) = w_j(n) + \left[\mu_{w_1}(n) f_1{}^2(n) sign\big(f_1(n)\big)\hat{x}_{j1}(n) + \mu_{w_2}(n) f_2{}^2(n) sign\big(f_2(n)\big)\hat{x}_{j2}(n)\right] \#(21)$$

Where step size parameter $\mu_{w_j}(n)$ is calculated as: -

$$\mu_{w_j}(n) = \frac{\mu_w}{\left\|\hat{x}_{j1}(n) + \hat{x}_{j2}(n)\right\|^2} \#(22)$$

μ_w is experimentally determined by extensive simulations.

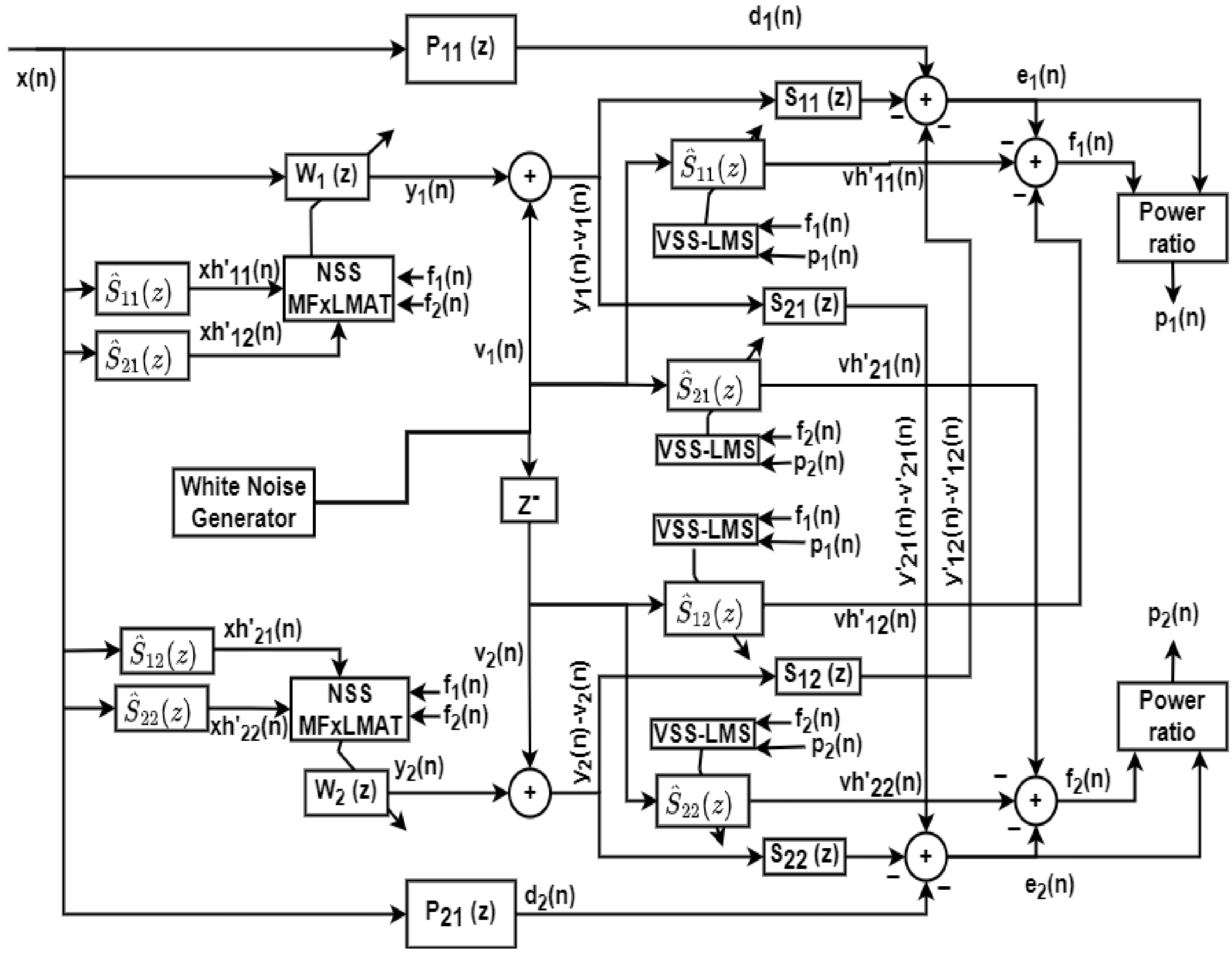

Figure 9: Proposed method – 4, NSS MFxLMAT & VSSLMS.

4. Section-IV: Computational Complexities

Any algorithm's implementation in real-time applications significantly depends upon computational complexity. **Table *1*** shows summary of computational complexities for various existing and proposed methods discussed in this paper.

Table 1: Computational Complexities.

Methods	$\times, \div, \sqrt{}$	+, -	Total
Eriksson's method	$16M+8L_w+4$	$18M+6L_w-6$	$34M+14L_w-2$
Akhtar's method	$16M+8L_w+22$	$18M+6L_w+6$	$34M+14L_w+28$
Ahmed's method	$24M+14L_w+81$	$28M+14L_w+34$	$52M+28L_w+115$
Yang's method	$18M+8L_w+4K+40$	$20M+6L_w+4K+12$	$38M+14L_w+8K+52$
Jabeen's method	$4L_w^2+4M^2+24M+14L_w+4K+34$	$4L_w^2+4M^2+18M+6L_w+4K+12$	$8L_w^2+8M^2+42M+20L_w+8K+46$
Proposed method – 1	$4L_w^2+16M+14L_w+22$	$4L_w^2+18M+6L_w+6$	$8L_w^2+34M+20L_w+28$
Proposed method – 2	$16M+8L_w+26$	$18M+6L_w+10$	$34M+14L_w+36$
Proposed method – 3	$16M+8L_w+30$	$18M+6L_w+6$	$34M+14L_w+36$
Proposed method – 4	$2L+16M+6L_w+36$	$4L+18M+6L_w+4$	$6L+34M+12L_w+40$

5. Section-V: Simulations and Discussions

This section discusses results of extensive MATLAB simulations carried out to validate the superior performance of proposed methodologies by comparing them with existing methods as mentioned below:

- Erikson's method [11]
- Akhtar's method [12]
- Ahmed's method [13]
- Yang's method [14]
- Jabeen's method [16]

Mean Noise Reduction (MNR_k) and Relative Modeling Error (ΔS_{kj}) are two performance metrics used for comparison of all algorithms under investigation. The MNR_k is defined as: -

$$MNR_k(n) = E\left\{\frac{A_{e_k}(n)}{A_{d_k}(n)}\right\} \#(23)$$

where $A_{e_k}(n)$ is measurement of absolute value of disturbance signal and $A_{d_k}(n)$ is absolute value of residual error, both measured at k^{th} error microphone, calculated as: -

$$A_{e_k}(n) = \lambda A_{e_k}(n-1) + (1-\lambda)|e_k(n)| \#(24)$$

$$A_{d_k}(n) = \lambda A_{d_k}(n-1) + (1-\lambda)|d_k(n)| \#(25)$$

On the other hand, the value of ΔS_{kj} is calculated as given in (26)

$$\Delta S_{kj}(n) = 20\log_{10}\frac{\|s_{kj}(n) - \hat{s}_{kj}(n)\|}{\|s_{kj}(n)\|} \#(26)$$

Using data from [4], original primary $P_{ki}(n)$ and secondary $S_{kj}(n)$ acoustic paths are taken as FIR filters. Values of various fixed parameters used for simulations in this paper are given in **Table *2***. Extensive simulations have been carried out to determine appropriate values for various controlling parameters to attain best results and these values are given in

Table *3*.

Modeling filters $\hat{S}_{kj}(n)$ in all proposed methods are adapted through VSSLMS algorithm which has stability issue at start when step size is smaller [31]. To avoid instability, modelling filters $\hat{S}_{kj}(n)$ are initialized by offline modelling until the modeling error is dropped to -5 dB instead of null vector [32].

Cases 1-3 of this section discuss performance of proposed algorithms under stationary environment with varying impulsive input (**Error! Reference source not found.**). Case – 4 presents performance for non-stationary environment: -

- Case – 1: Moderate impulsive input (α=1.85)
- Case – 2: High impulsive input (α=1.65)
- Case – 3: Very high impulsive input (α=1.45)
- Case – 4: Non-Stationary Environment

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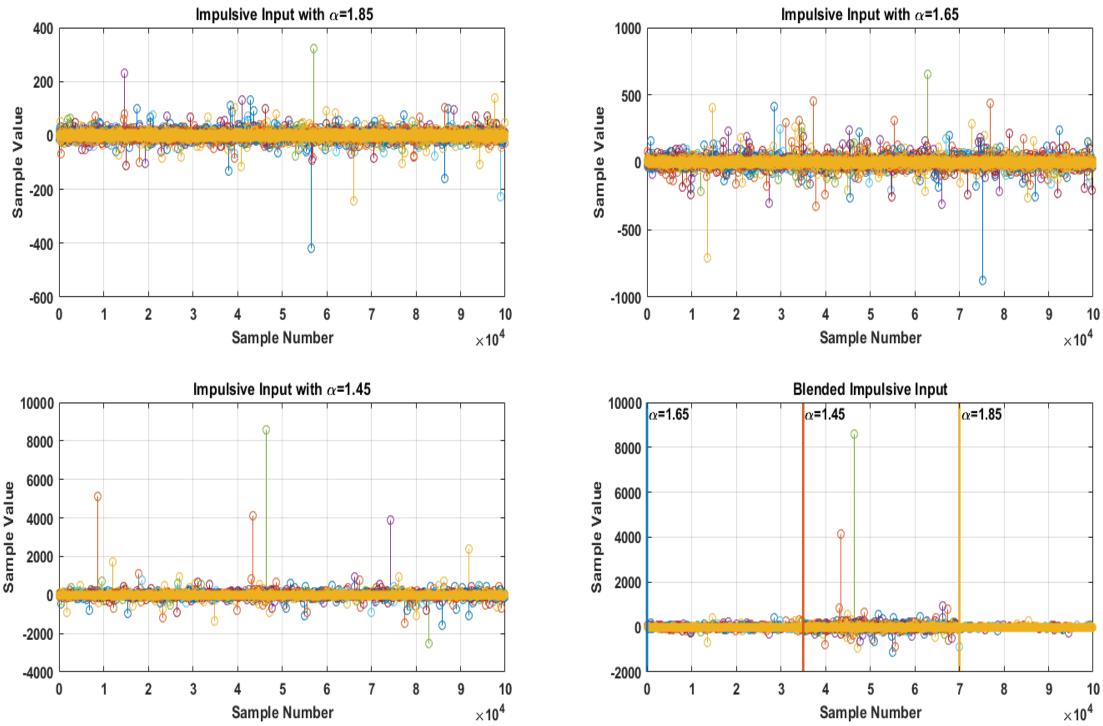

Figure 10: (a) Moderate impulsive input (α=1.85), (b) High impulsive input (α=1.65), (c) Very High impulsive input (α=1.65), (d) Blended impulsive input.

Table 2: Various simulations parameters.

MC ANC system with OSPM			**IN [$x_r(n)$]**		
Parameter	Symbol	Value	Parameter	Symbol	Value
Primary paths tap size	L	48	Total samples	N	100,000
Secondary paths tap size	M	16	Total realizations	Avg	10
Control filters tap size	L_w	32	Characteristic exponent	α	1.85, 1.65, 1.45
OSPM filters tap size	M	16	Other parameters	γ	1
				C	0
				δ	0

Table 3: Controlling Parameters.

Methods	Case – 1	Case – 2	Case – 3	Case – 4
Eriksson's method	μ_w = 5e-7 μ_s = 1e-4 λ = .99	-	-	-
Akhtar's method	μ_w = 3e-7 μ_{s_min} = 7.5e-5 μ_{s_max} = 7.5e-4 λ = .99	-	-	-
Ahmed's method	μ_1 = 2.5e-3 μ_2 = 9.5e-3 α = .997 γ_{min} = .3 γ_{max} = .9 λ = .999	-	-	-
Yang's method	μ_w = 1e-7 μ_h = 1e-4 α = .005 λ = .9999	μ_w = 1e-7 μ_h = 1e-4 α = .0025 λ = .9999	μ_w = 1e-8 μ_h = 1e-8 α = .0015 λ = .9999	μ_w = 1e-8 μ_h = 1e-8 α = .0015 λ = .9999
Jabeen's method	δ_1 = 1e5 δ_2 = 4.5e4 μ_h = 1e-4 λ = .99	δ_1 = 1e5 δ_2 = 6.5e4 μ_h = 1e-4 λ = .999	δ_1 = 1e6 δ_2 = 6.5e5 μ_h = 1e-6 λ = .99	δ_1 = 1e6 δ_2 = 6.5e5 μ_h = 1e-6 λ = .99
Proposed method - 1	δ = 5e4 μ_{s_min} = 1e-4 μ_{s_max} = 7e-3 λ = .99	δ = 5e4 μ_{s_min} = 1e-4 μ_{s_max} = 7e-3 λ = .99	δ = 5e5 μ_{s_min} = 1e-4 μ_{s_max} = 7e-3 λ = .99	δ = 5e5 μ_{s_min} = 1e-4 μ_{s_max} = 7e-3 λ = .99
Proposed method - 2	μ_{w_min} = 1e-6 μ_{w_max} = 1e-4 μ_{s_min} = 7.5e-4 μ_{s_max} = 7.5e-3 λ = .99	μ_{w_min} = 1e-6 μ_{w_max} = 1e-4 μ_{s_min} = 7.5e-4 μ_{s_max} = 7.5e-3 λ = .99	μ_{w_min} = 1e-7 μ_{w_max} = 1e-5 μ_{s_min} = 7.5e-6 μ_{s_max} = 7.5e-3 λ = .99	μ_{w_min} = 1e-7 μ_{w_max} = 1e-5 μ_{s_min} = 7.5e-6 μ_{s_max} = 7.5e-3 λ = .99
Proposed method - 3	μ_w = 1e-7 μ_{w_max} = 7e-2 μ_{s_min} = 1e-4 λ = .999	μ_w = 1e-9 μ_{w_max} = 7e-2 μ_{s_min} = 1e-4 λ = .999	μ_w = 5e-13 μ_{w_max} = 7e-2 μ_{s_min} = 1e-6 λ = .999	μ_w = 5e-13 μ_{w_max} = 7e-2 μ_{s_min} = 1e-6 λ = .999
Proposed method - 4	μ_w = 5e-3 μ_{s_min} = 1e-4 μ_{s_max} = 7e-3 λ = .99	μ_w = 5e-3 μ_{s_min} = 1e-4 μ_{s_max} = 7e-3 λ = .99	μ_w = 9.5e-4 μ_{s_min} = 1e-4 μ_{s_max} = 7.5e-3 λ = .99	μ_w = 9.5e-4 μ_{s_min} = 1e-4 μ_{s_max} = 7.5e-3 λ = .99

Case – 1 : Moderate Impulsive Input (α=1.85)

To begin with simulation part, all reported algorithms [11, 12, 13, 14, 16] are subjected to moderated impulsive noise (α=1.85) for MC ANC with OSPM. Figure 11 shows comparison of relative modelling error $\Delta S_{kj}(n)$ and mean noise reduction ($MNR_k(n)$) of various existing techniques. Figure 11 (a) shows that Yang's method exhibits fastest convergence at n=10,000 and achieving lowest value of $\Delta S_{kj}(n) = -25\ dB$ while MNR curve depicted in Figure 11 (b) shows that Jabeen's method achieved convergence at n=20,000 with lowest steady state value (0.35 dB) among all the existing methods [11, 12, 13, 14, 16]. Since, Yang's and Jabeen's methods outperform other exiting methods hence, only these two methods are being employed in future simulations and compared with algorithms proposed in this paper.

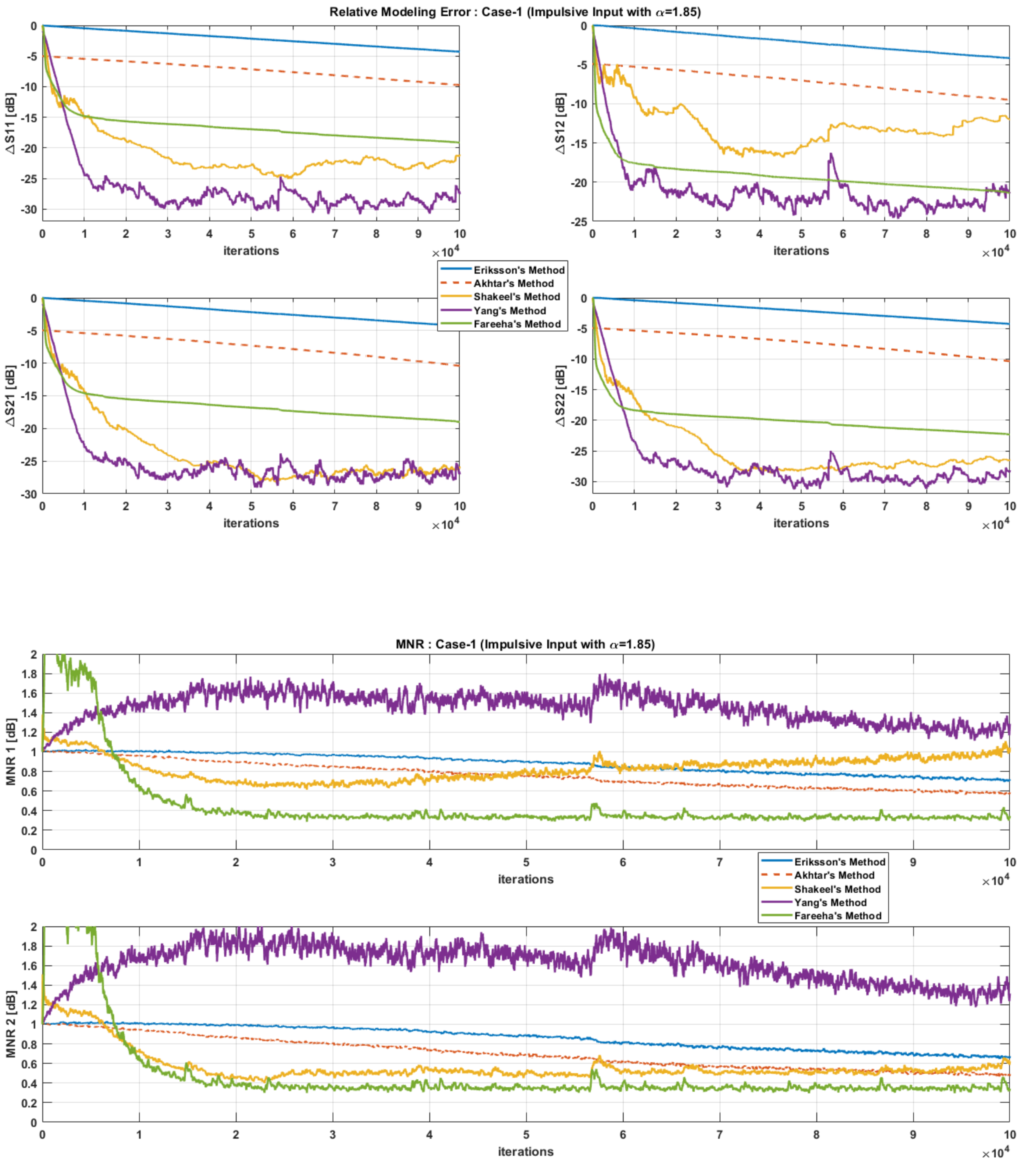

Figure 11: Simulation Results - Existing Methods, Case-1. (a) ΔS (b) MNR.

Although, Jabeen's method [16] exhibited best performance in terms of noise reduction among existing techniques as shown in Figure 11 (b), however, this exceptional performance was achieved at the cost of higher computational complexity due to use of FxRLS-FxRLS algorithm in both, control $W_j(n)$ as well as modelling $\hat{S}_{kj}(n)$ filters. To overcome this additional computation load while achieving similar performance, we developed our first proposed method which is a combination of FxRLS-VSSLMS algorithms (Proposed method - 1). This proposed method has quite less computational complexity (**Table *1***) as compared to Jabeen's method but in the noise reduction, it even surpasses Jabeen's method in terms of convergence speed, robustness to impulsive input and lower steady state value (Figure 12). MNR curve depicted in Figure 12 (b) shows that Proposed FxRLS-VSSLMS achieved convergence at n=8000 with steady state value of 0.27 dB.

Good results of Proposed FxRLS-VSSLMS algorithms motivated us to further develop our second proposed algorithm, VSSLMS-VSSLMS (Proposed method - 2), which has even lesser complexity (**Table *1***) than our proposed method 1 and still achieves same steady state MNR values (0.27 dB) as in the case of Proposed method 1, however, with reduced convergence speed at n = 16,800 as shown in Figure 12 (b).

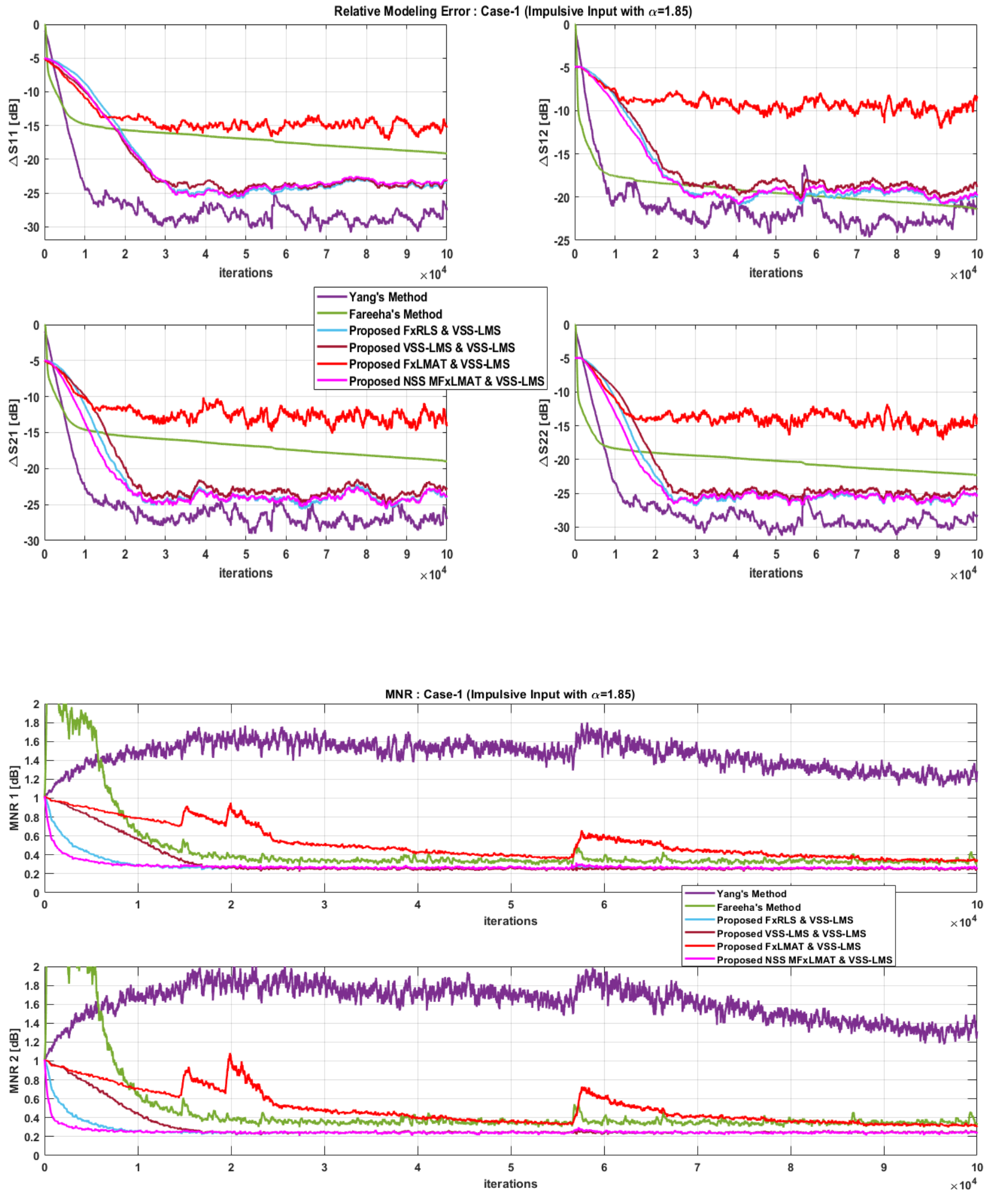

Figure 12: Simulation Results, Case-1. (a) ΔS (b) MNR.

To combine the positive aspects (e.g. low steady state error and robustness) in both the proposed methods – 1 and 2 and cater for their negative aspects (e.g. high computational complexity in Proposed FxRLS-VSSLMS and slow convergence in Proposed VSSLMS-VSSLMS), a third method is proposed. This third proposed method combines FxLMAT (as used by Khan and colleagues against IN [30]) with VSSLMS algorithms (Proposed method – 3). This method when implied in a MCANC system in the presence of IN, although achieved steady state value (0.35 dB) as in Jabeen's method, however, its convergence is very slowly, achieved at n=50,000. Moreover, Proposed FxLMAT-VSSLMS does not show robustness to impulsive nature of input noise, (Figure 12 (b)). Hence, lastly, a modified version of FxLMAT is presented in proposed method 4 as combination of NSS MFxLMAT-VSSLMS. Figure 12 (b) shows that this proposed NSS MFxLMAT-VSSLMS demonstrates best results among all techniques with fastest convergence at n=4000 and same steady state value of MNR = 0.27 dB with least complexity (**Table *1***).

Case – 2: High Impulsive input (α=1.65)

For high IN, similar results are obtained as in Case-1 of moderate IN. Simulation results shown in Figure 13 (a) confirms that Yang's method [14] extended to MC again gives best result in reduction of relative modelling error $\Delta S(n)$ = -30 dB while proposed algorithms yet again give best MNR curve but with less computational complexity (**Table *1***). It is evident from Figure 13 (b) that proposed methods – 1, 2 & 4 achieve lowest steady state MNR value of 0.24 dB. Proposed VSSLMS-VSSLMS exhibits slower convergence at n= 13500, similar to its performance in case – 1. Proposed FxRLS-VSSLMS and Proposed NSS MFxLMAT-VSSLMS show faster convergence at n= 8000 and n=4000, respectively.

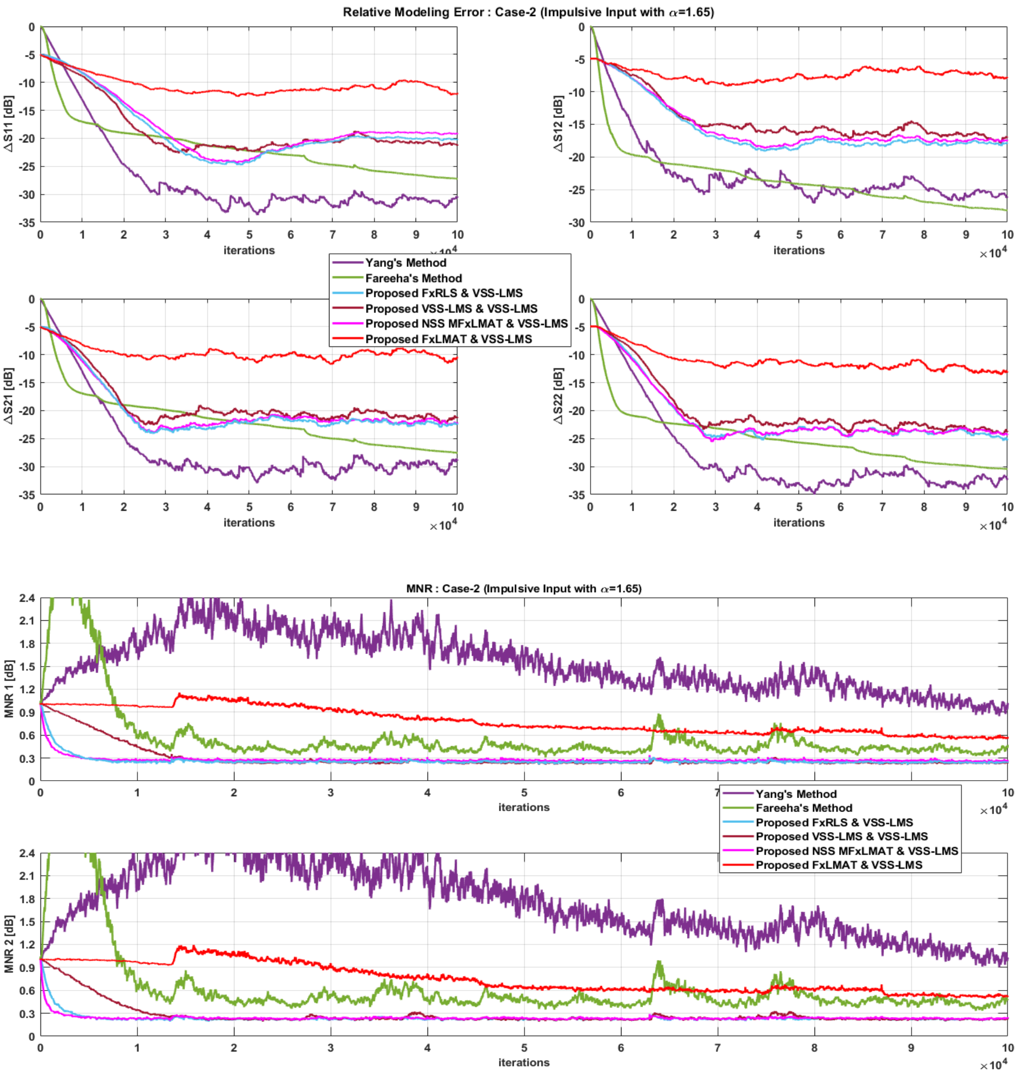

Figure 13: Simulation Results, Case-2. (a) ΔS (b) MNR.

Case – 3: Very High Impulsive input (α=1.45)

In this case, when the input noise becomes highly impulsive, Yang's method [14] consistently performed best (Figure 14 (a)) for reduction of relative modelling error $\Delta S(n)$= -30 dB. On the other end, MNR performance of Proposed VSSLMS-VSSLMS has deteriorated for this excessive IN (Figure 14 (b)). However, Proposed FxRLS-VSSLMS and Proposed NSS MFxLMAT yet again performed unswervingly best for MNR curve with fastest convergence at n=8000 and lowest steady state error of 0.22 dB and 0.28 dB respectively.

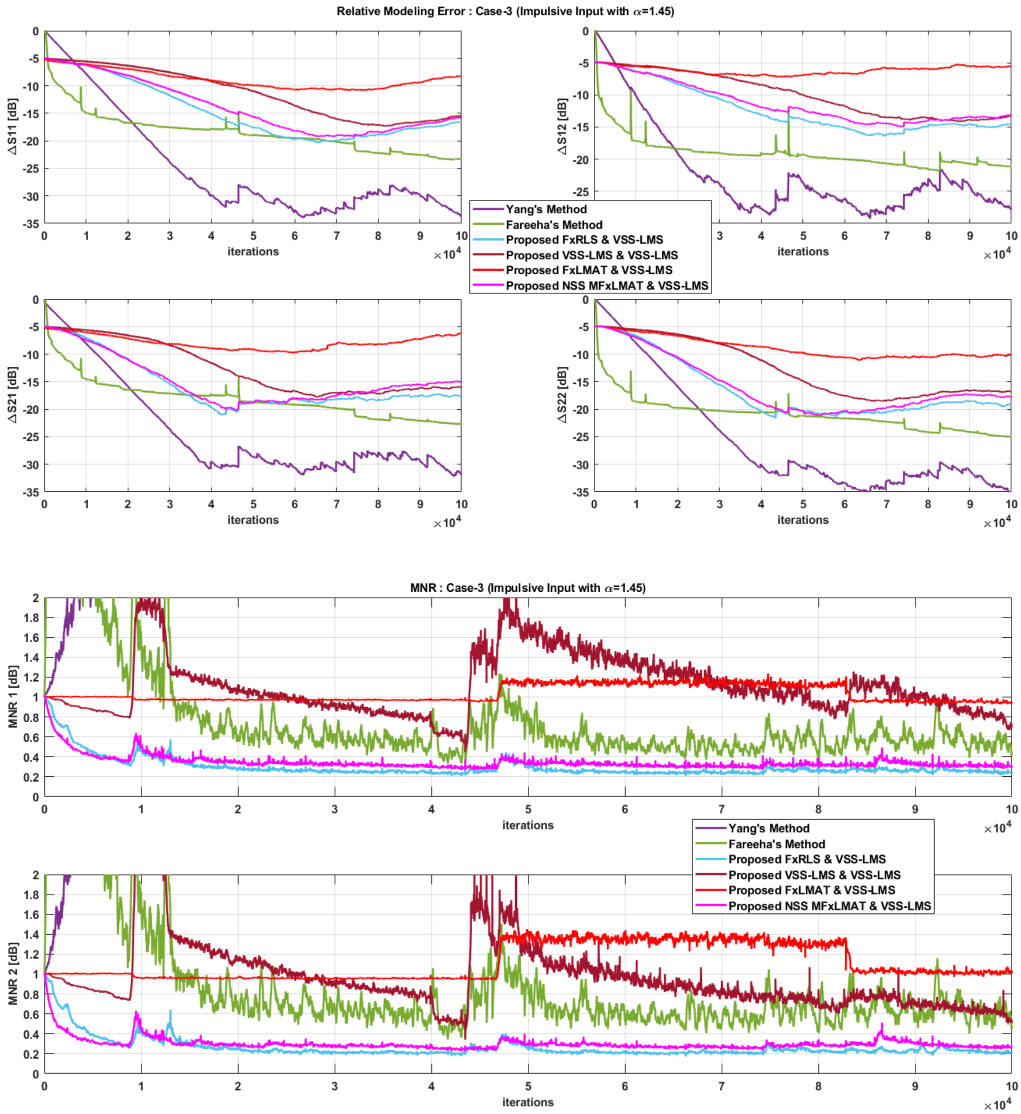

Figure 14: Simulation Results, Case-3. (a) ΔS (b) MNR.

Case – 4: Non-Stationary Environment

In our final evaluation, proposed methods are subjected to non-stationary environment to check for their robustness as follows:-

a. In first instance, all secondary paths are perturbed at iteration n=50,000 and very high IN (α=1.45) of case 3 is used as input to assess behavior of proposed algorithms.

b. In second trial, a blended impulsive input comprises of varying α is used as under *Figure 10* (d):-

$$\alpha = \begin{cases} 1.65 & ; \quad 0 < n < 35{,}000 \\ 1.45 & ; \quad 35{,}000 \le n < 70{,}000 \\ 1.85 & ; \quad 70{,}000 \le n \le 100{,}000 \end{cases}$$

Simulation results (Figure 15 & Figure 16) confirm robustness of proposed algorithms under non-stationary environment.Figure 15 (a) shows that only Yang's method, Proposed FxRLS-VSSLMS and NSS FxLMAT-VSSLMS converge after perturbation is encountered at n=50,000. Moreover, Yang's method consistently manifested lowest relative modeling error by reaching to -30 dB. Similarly, Figure 15 (b) shows that Proposed FxRLS-VSSLMS and NSS MFxLMAT-VSSLMS performed in same manner as in case – 3 (α=1.45). In this case, both the proposed algorithms have touched lowest steady state error of 0.20 dB and 0.22 dB respectively. It is important to note that after encountering perturbation at n=50,000, both algorithms took 8000 iterations again to converge at n=58,000 as in the beginning (n=0 to n=8000).

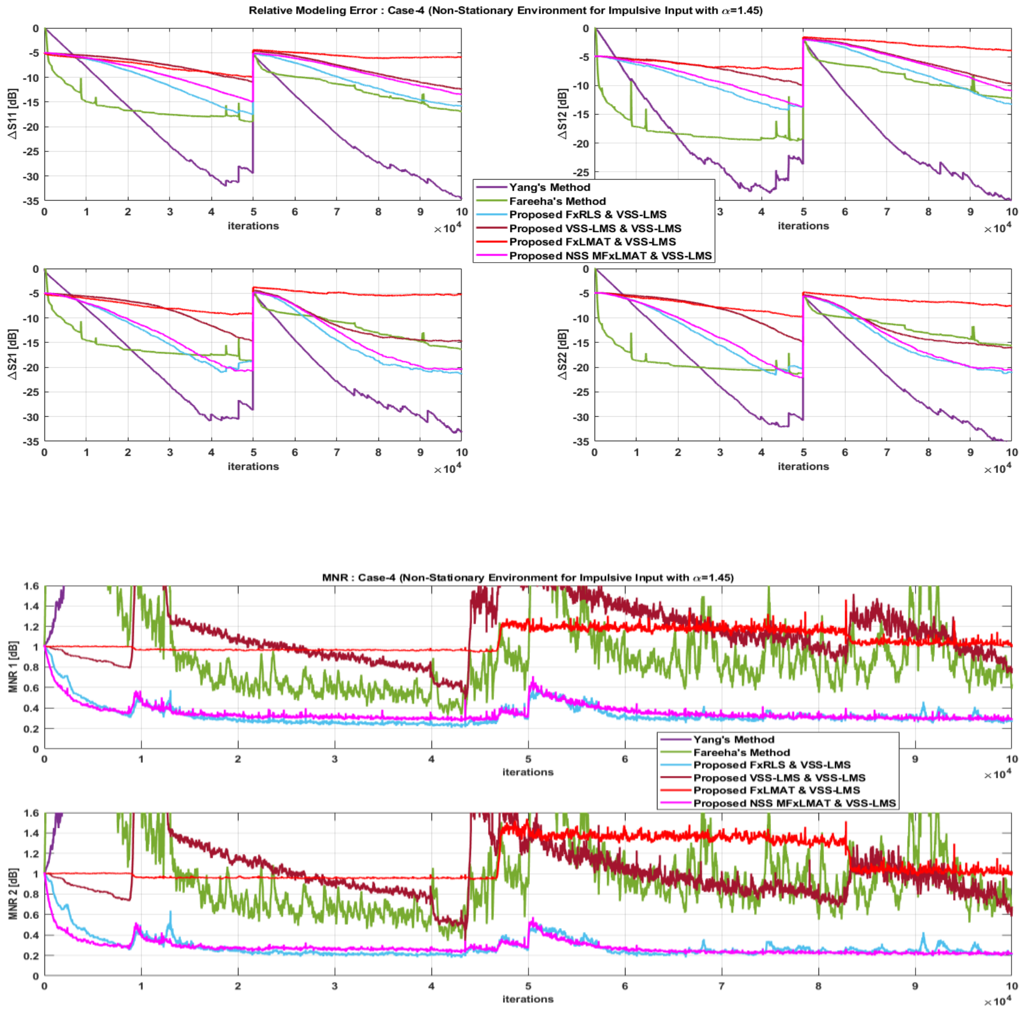

Figure 15: Simulation Results, Case-4 (α = 1.45). (a) ΔS (b) MNR.

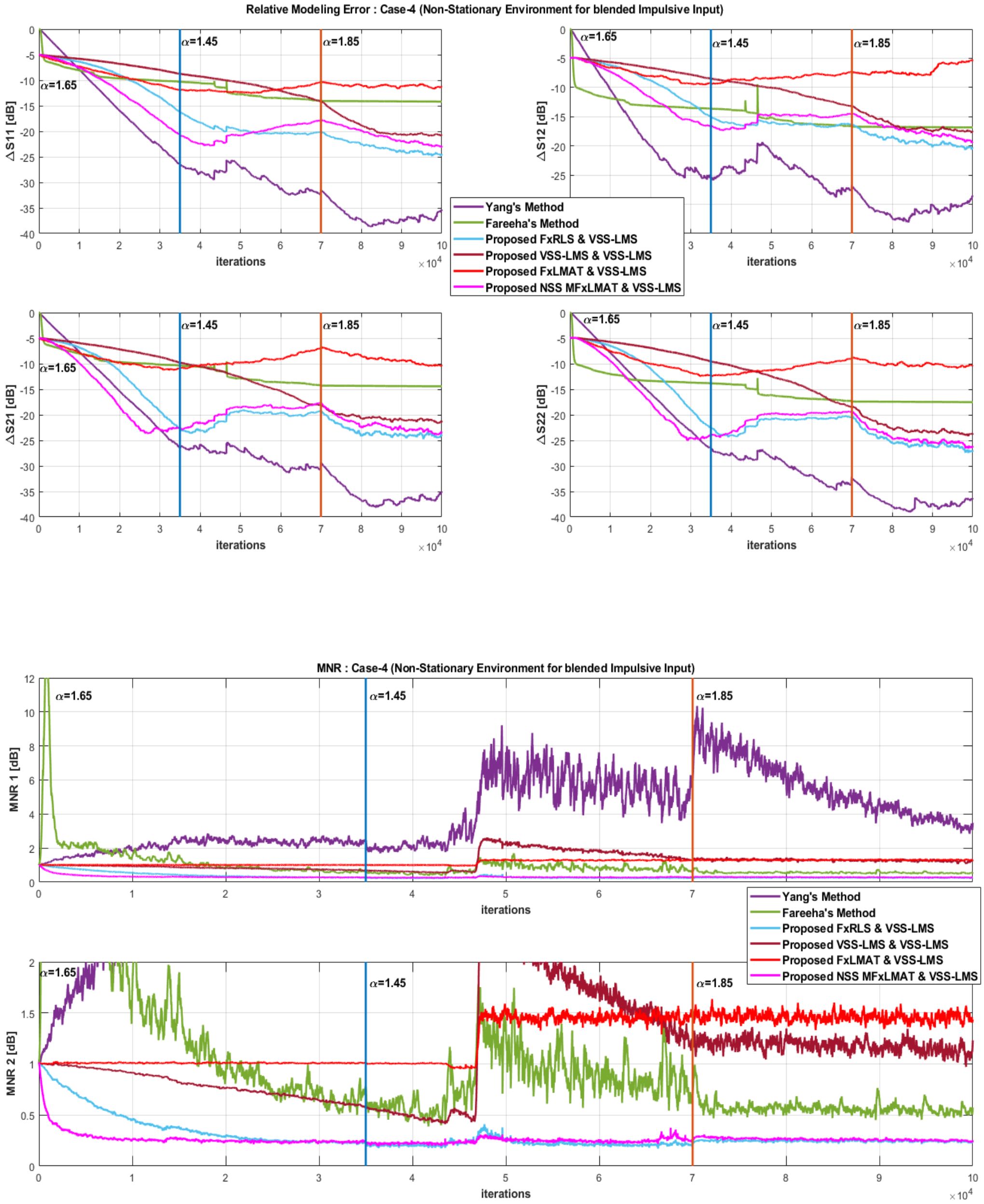

Figure 16: Simulation Results, Case-4 (blended input). (a) ΔS (b) MNR.

Figure 16 shows response to blended IN. At beginning n=0, high impulsive input (α=1.65) is used. At n=35000, it is changed to very high IN (α=1.45) and at n=70000, to moderate IN (α=1.85). It is evident from simulation results depicted in Figure 16 (a) that Yang's method continue to perform best for relative modeling error. A slight change is observed in convergence pattern at swap over points in relative modeling error. Figure 16 (b) illustrates MNR for blended IN. Proposed FxRLS-VSSLMS and NSS MFxLMAT-VSSLMS once again reached to lowest steady state error of 0.22 dB and 0.25 dB, respectively.

Only a minor disturbance is noticed at swap over points (n=35000 and n=70000).

6. Conclusion

In this paper, four new methods are proposed to mitigate IN in MC ANC system employing OSPM for the first time under stationary as well as non-stationary environment. The outcomes of the simulations show that the proposed algorithms offer quicker convergence and lowest steady state error for MNR than existing approaches with comparable modeling accuracy. Proposed NSS MFxLMAT-VSSLMS achieved same performance as par with high order complex FxRLS algorithm with much less computational complexity. There is a room of improvement available in modeling accuracy which is a task of future work.

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