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# An Improved All-Pass Filtered x Least Mean Square Algorithm

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**ABSTRACT**

In this advanced world the usage of cutting-edge technologies in daily life increase day by day, whereby, acoustics noise also increases thereby affecting our life. So, an urgent requirement is to reduce this noise and improve the quality of life. Several Active noise control (ANC) systems using Artificial Neural Networks (ANN) are present but in limited performance. This paper is focused to develop an adaptive all-pass filtered x least square algorithm for a single-channel narrowband active noise control system using Nonlinear autoregressive with external (exogenous) input (NARX). The novelty of this research is that the All-pass filtered x LMS (APFxLMS) algorithm is introduced to the system without the need to identify the secondary path. Here the first-order all-pass filters with a single parameter are used to improve the convergence of the LMS algorithm. The results show that the proposed method performance is better in terms of regression and mean square error and on comparison with the recent method through numerical simulation shows that the proposed method is simpler to implement, and it achieves fast convergence speed.

**Key words:** Adaptive system, Active noise control (ANC), All-Pass Filtered x Least Means Square Algorithm (APFxLMS) and Artificial Neural Network (ANN), Nonlinear Autoregressive with External (Exogenous) Input (NARX).

## 1. INTRODUCTION

ANC framework is a system to reduce acoustic noise using a signal which is exactly in opposite phase of the unwanted noise signal but same in amplitude [1,2]. There are many kinds of adaptive ANC systems developed in this modern age because of the exponential increment of noise pollution and ineffectiveness of passive procedures for noise attenuation [1–6]. This procedure has been effectively connected to warming, ventilating, and cooling frameworks [4,5], exhaust and engine noise [4,6], headsets [4,6], and planes [4]. The most popular ANC system filtered x least mean square (FxLMS) algorithm using linear finite impulse response (FIR) filter [2] with secondary path identification, work well in some cases but performs poorly and even fails to work for nonlinear cases [7]. Several ANC systems are developed in recent era which does not required secondary path identification, also perform poorly in some cases. Some of researcher used fuzzy logic methodology to reduces the noise [3], fuzzy logic also used in numerous research work for example it can be used in voltage stability [25] or risk management system [26] etc. To solve these nonlinear cases in ANC system, several nonlinear structures and algorithms are proposed over past fifteen years [8-20]. Most widely used ANN system is functional link artificial neural network (FLANN) filter. FLANN filter is used in many cases, such as feedforward ANC, feedback ANC, single channel ANC, multichannel ANC. There are other different kinds of nonlinear ANN system for ANC system such as NARX system, Volterra system, bilinear system, etc. discussed widely in section 2. However, these systems have their limitations and the performance is not accurate and sometime fail to work and create computational complexity. Therefore, there is an urgent need to develop a robust and accurate ANN system for ANC. To simplify the computational complexity of APFxLMS algorithms [12] without secondary path identification is used to update the controller and corrective filter weights. This paper is focused to develop a robust NARX system using APFxLMS algorithm to reduce the inherent assurance between nonlinear coefficients and improve the performances of FLANN and its other modified versions. ANN widely used in many different areas such as legal procedure research work [27] and forecasting data file [28] also. This paper is organized by the introduction of historical development of ANN systems in Section 2. The proposed algorithm and the methodology are presented in section 3. In section 4, numerical simulation results are discussed, with the conclusion in Section 5.

## 2. HISTORICAL DEVELOPMENT

Use Snyder and Tanaka (1995) [8] proposed a versatile algorithm which empowers stable adjustment of the neural controller while giving the ability to keep up causality inside the control plan utilizing essential speculation of the linear filtered-x LMS algorithm. The neural network controller was demonstrated to have the option to make up for the presentation of sounds by the control actuator by creating a control signal, obtained from an unadulterated tone reference signal, which contains some degree of sounds. Likewise, the neural controller supposedly was ready to make up for a misshaped reference signal in a way better than that of a linear controller. The fundamental disadvantage concerning the utilization of the nonlinear neural network controller was an absence of consistency throughout and its presentation. Pavisic et. al. (1996) [9] built up a neural active noise controller which performs better compared to existing systems. They utilized a dynamic intermittent neural network to show the conduct of a current controller that uses a Least Mean Squares algorithm to limit an error signal. The neural controller adapts much better noise-reducing even for cases for which the network was not tailored. It also performs well with noisy functions and even with pure white noise. Debi Prasad Das and Ganapati Panda (2004) [10] proposed a novel filtered S least mean square (FSLMS) algorithm-based ANC structure, which perform as a nonlinear controller, utilizing the FLANN as the essential structure. They improved their proposed algorithm with a fast implementation scheme. The proposed fast FSLMS based nonlinear ANC is better than other proposed algorithms both regarding the steady state mean square error and computational complexity. Krukowicz (2010) [11] introduced an active noise control algorithm dependent on a neural network. It was based on a nonlinear input-output framework identification model with a nonlinear primary path, utilizing the NARMAX framework identification model. In various convenient applications, the acoustic noise delivered from dynamical structures is nonlinear and deterministic or stochastic, concealed, and non-Gaussian. It has been observed that the primary frameworks used to control such noise show degradation in execution. Moreover, the actuators of ANC framework have a nonminimum phase response. A straight controller under such conditions cannot demonstrate the opposite of the actuator and yields poor execution. In numerous applications, the acoustic noise produced from dynamical frameworks is nonlinear and deterministic or stochastic, hued, and non-Gaussian. It has been accounted for that the linear procedures used to control such noise display errors in execution. Also, the actuators of ANC framework throughout have a nonminimum-stage reaction. A linear controller under such circumstances cannot show the reverse of the actuator, and thus yields erroneous results. To maintain a strategic distance from this approach there are some new research which are now being discussed.

Tsuyama and Maeda (2002) [13] connected a neural network for active noise control and utilized the simultaneous perturbation method. It was used as a learning standard of the neural network which does not require an estimation of the secondary-path to decrease a 200Hz sinusoidal wave noise and a hand-constrained white noise. Zhou et.al. (2009) [14] proposed a novel FLANN based simultaneous perturbation stochastic approximation (SPSA) algorithm. The algorithm performs as a nonlinear mode-free (MF) controller utilizing the FLANN as the fundamental structure and improves noise work without utilizing subordinate of the noise work. It also does not require any estimation of the secondary path. Zhang and Ren (2010) [15] proposed a novel ANC framework dependent on neural networks. It performs for nonlinear ANC frameworks without the identification of secondary path, by presenting virtual primary noises with the assistance of neural networks. This approach does not necessitate to constrict the noise and does not require the elements information of the primary and secondary path model. On comparison with old-style noise control performance, it has a simple structure and minimal calculation unpredictability. The security of the entire framework is demonstrated by the Lyapunov hypothesis. Sicuranza and Carini (2011) [16] proposed an augmentation of the notable FLANN channel utilizing trigonometric developments. It incorporates reasonable cross-terms, i.e., results of info tests with various time steps. The resulting FLANN channel still has a place with the class of filters whose yield depends linearly on the filter coefficients and whose nonlinear extensions fulfill the time-step property. Behera et.al. (2014) [17] exhibited the partition of tonal and the disordered signal is rectified by a versatile waveform union technique. In this approach anti-noise of tonal segment is delivered by another waveform synthesizer to sustain a nonlinear controller. It utilizes FLANN or Volterra channel to create the anti-noise of the disordered part of the noise which first isolates the disordered signal from the noise mixture. The evaluated turbulent signal was utilized in a FLANN/Volterra based nonlinear controller. This algorithm utilized a narrow band controller and a broadband controller. Subsequently, it is called a hybrid controller and it demonstrated more noteworthy noise reduction capacity contrasted with numerous recently developed algorithms, like, FXLMS, FSLMS, mixture ANC.

Zhao et. al. (2016) [18] proposed CNFSLMS algorithm-based FLANN filter, leading to control the tradeoff between convergence speed and steady-state mean square error of the NFSLMS algorithm. It offers both fast convergence rate and low steady-state error, by supplanting the sigmoid capacity with the altered Versorial work. The tailored CNFSLMS (MCNFSLMS) algorithm with low computational complexity is a better choice than others. It includes two new adaptive algorithms with various step sizes, CNFSLMS and MCNFSLMS algorithms. The MCNFSLMS algorithm is in the same class as the CNFSLMS, with less computational unpredictability for nonlinear ANC frameworks with the LSP and NSP. Le et. al. (2018) [19] proposed a novel bilinear

FLANN (BFLANN) channel for the nonlinear ANC and displayed the dependability of the BFLANN channel and generalized FLANN (GFLANN) channels based nonlinear ANC. The outcome of the nonlinear ANC framework dependent on the BFLANN channel is superior to that of the GFLANN and FLANN channels. Li et.al (2018) [20] additionally presented the nonlinear adaptive exponential functional link artificial neural networks(E-FLANN) channel to improve the noise reduction ability of the useful connection FLANN in nonlinear active noise control (NANC) framework. The proposed algorithm was developed to stay away from substantial computational weight at the nonlinear secondary path (NSP) and poor intermingling result in solid nonlinearity frameworks with the channel-diminished askew structure (GE-FLANN-CRD) for NANC framework. The outcome of the channel has been upgraded by adjusting the reasonable cross-terms and versatile exponential factor. In view of the askew channel structure, this GE-FLANN-CRD channel was effectively incorporated with the channel bank structure. The proposed GE-FLANN-CRD channel offers preferable control execution over the FLANN, E-FLANN and GFLANN channels. Luo et. al. (2018) [21] improved FLANN (IFLANN) channel and simplified IFLANN (SIFLANN) channel to diminish the computational complexity. Further, the filtered-error least mean square (FELMS) algorithm is considered in the NANC framework by including a remedial channel before trigonometric capacity extension. It offers reasonable cross-term defer tests and balance the coefficients of nonlinear estimation, IFLANN and SIFLANN channels outperforms FLANN, GFLANN, CFLANN and second request EMFN channels. Md. Z. Zakaria et al. (2018) [22] presented the expansion of the MOODE algorithm to get an adequate and adjusting nonlinear auto-regressive moving average with exogenous input (NARMAX) model. They (2018) [23] also presented the identification of a flexible beam system using Nonlinear Autoregressive Moving Average with Exogenous input (NARMAX) model. The methodology integrates with Multi-Objective Optimization Differential Evolution (MOODE) algorithm. Guo et al. (2018) [24] developed new control algorithm that resulted in reduction of computational complexity. It showed the noise at the canceling point might be approximated by the function expansion filters when the secondary path is modeled because the second order Volterra series. In addition, two new function expansion forms, the even mirror Fourier nonlinear filter with a linear finite-impulse response section and therefore the Chebyshev filter, are explored. They are incorporated to process the nonlinearities in the NANC system using the filtered-x least mean square and filtered error least mean square algorithm structures.

## 3. APFXLMS USING NARX

The novelty of the proposed APFxLMS system [12] is the use of the all-pass filter in place of the estimated secondary path transfer function. The all-pass filter is generally an IIR (Infinite Impulse Response) filter. Here the magnitude response does not change over its entire frequency, but its phase response is changeable. For this reason, the all-pass filter is known as a phase shifter or equalizer. Now this proposed system is realized with the help of the NARX and the block diagram is shown in fig. 1. Here the primary-path P(Z) is from the noise source to the error microphone, and the secondary path S(Z) is from the canceling loudspeaker to the error microphone. The NARX controller is used to generate the control signal y(n) without the secondary path identification. Fig. 2 shows the schematic diagram of the NARX controller and the step of the design of this network is analysis below.

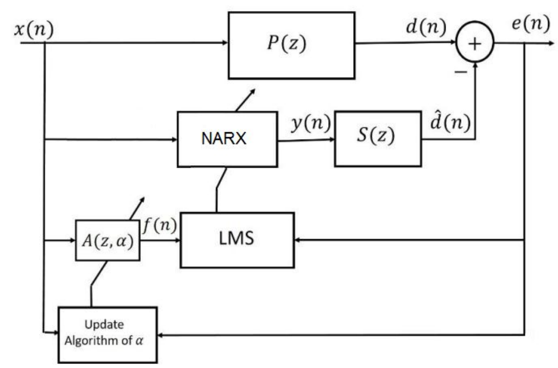



**Figure 1:** Block diagram of APFxLMS using NARX

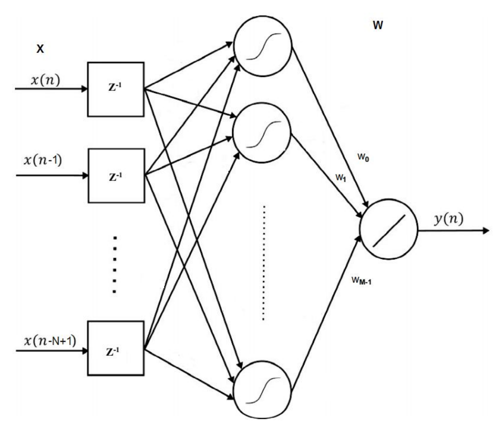



**Figure 2:** Schematic diagram of NARX

### 3.1 Steps of preparing NARX

The steps of preparing the NARX in Neural Network (NN) system:

1. Selection of the system
2. Arrangement of the system.
3. Preparing the system

### 3.2 Selection of the system

First, the system needs to select. To do this, the command to open the NN Start the GUI with this command: nnstart. The NN fitting tool compartment is shown (Fig. 3). The next step is to choose the NARX after selecting the dynamic time series and it is shown in Fig. 4 and after that need to provide the input and the output datas in NARX.

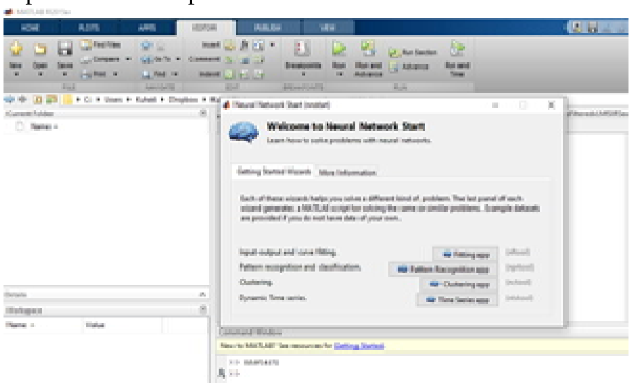



**Figure 3:** NN fitting tool compartment

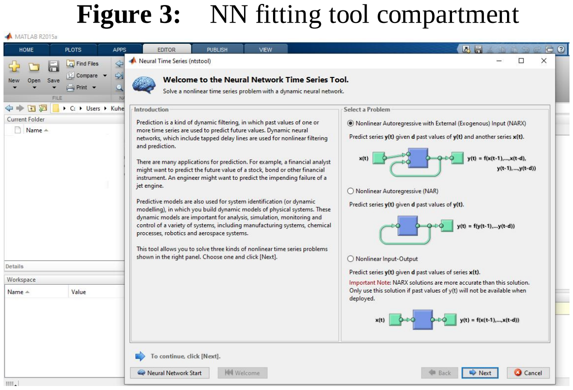



**Figure 4 :** Choosing the NARX Control System

### 3.3 Arrangement of the system

These include a methodical process and evaluation that incorporates the inheritance of functions. To build up the estimation models, a back-proliferation neural network was used in this exploration. A preparation set of 26 esteems; a testing set of 7 esteems and an approval set of 7 esteems. Here the training set at 70%, Validation at 15% and testing also at 15% (see Fig. 5) and in Fig. 6 the design of NARX has appeared.

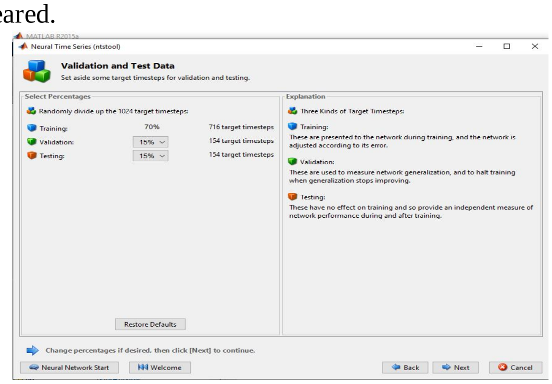



**Figure 5:** Collecting data in NARX

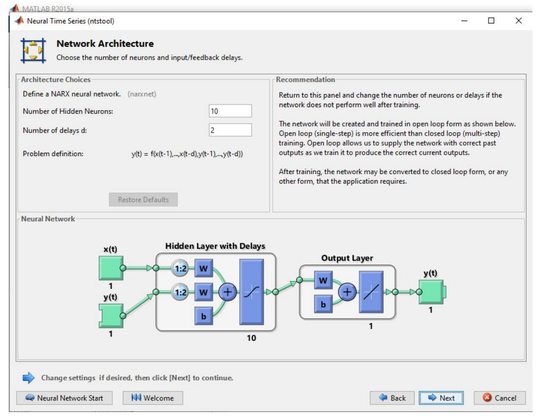



**Figure 6:** The Architecture of NARX

### 3.4 Preparing the system

This system starts by including choices of picking a ton of affiliation loads for each layer. Every neuron decides its total capacity and hence registers its exchange capacity system, which relates to its outcome. This process works in forward direction only.

A lot of registered results are interpreted in the result layer. For each planning part in the result layer, an error is addressed, each focus on a deviation of the modified result from the perfect result.

Utilizing a learning rule, the errors are brought back through the covered-up layer(s) and the association necessities are balanced and refreshed accordingly.

Feed-forward algorithm starts from the very beginning once more. New result regard registered and the abovementioned cycle proceeds until an ideal setting of preliminaries is obtained. The outcome of the leadup was to setup loads that restricts the mistakes as the result neurons initially produce factors that differ fundamentally from the proper results. During the process of preparation, both the information sources (communicating to point parameters) and yields (communicating to the setups) are shown to the system typically for numerous cycles (Fig. 7)abbreviation “e.g.,” means “for example” (these abbreviations are not italicized).

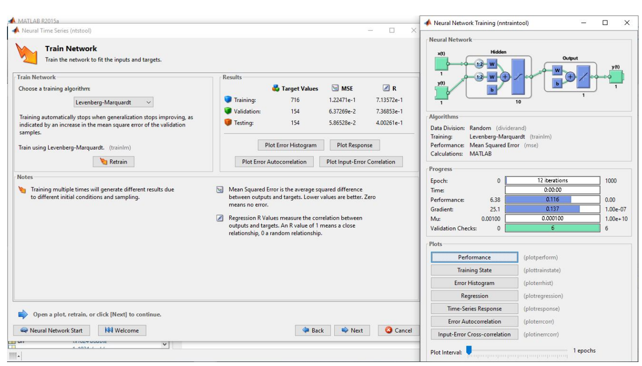



**Figure 7:** Preparing of NARX

## 4. RESULTS AND DISCUSSIONS

### 4.1 Performance Test

When the training of multilayer neural networks was completed, the network performance was checked to work out if any changes got to be made to the training process, the specification, or the data sets. First, the training record, tr, returned from the training function. Then the value tr.best epoch indicated the iteration at which the validation performance reached a minimum. The training for this network continued for 27 more iterations before the training was stopped. This result did not indicate any major problems with the training as seen in Figure 8. Similarly, the validation and test curves are very similar. If the test curve had increased significantly before the validation curve increased, then it's possible that some over fitting may need occurred. This is however not the case during this model. From the Fig. 8, a good validation result has been obtained.

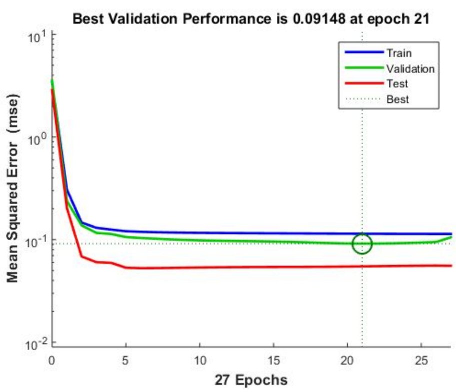



**Figure 8:** Results of Mean Squared Error (MSE)

### 4.2 Mean Squared Error and Regression Results

The mean squared error is that the average squared difference between outputs and targets. The system is better if the estimation is lower and if it is zero that means no error. On the other hand, Regression values measure the relationship with outputs and targets. If the value of R is nearly 1 or 1 that means, there is a very close relationship, if it is 0 then there is an irregular relationship. The smaller the value of the regression, the smaller the difference between the outputs and targets. The regression values are near to zero thus showing better execution results shown in table 1.

**Table 1:** Mean Squared and Regression Results

| Validation Stages | Mean squared and regression results | |
|---|---|---|
| | *Mean Squared Error* | *Regression* |
| Training | 1.04672 | 0.96837 |
| Validation | 0.91482 | 0.93833 |
| Testing | 0.84314 | 0.92921 |

In this section in validating the network is to get a regression plot which measure the connection between outputs and targets. If the training was perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice. Fig. 9 illustrates the regression results. The following regression plots display the network outputs with reference to targets for training, validation, and test sets. For the best result, the data should be making a 45-degree line, where the framework output data are equal to the target. In this case, the fit is reasonably good for all data sets, with R values in each case is 0.92 or above of it.

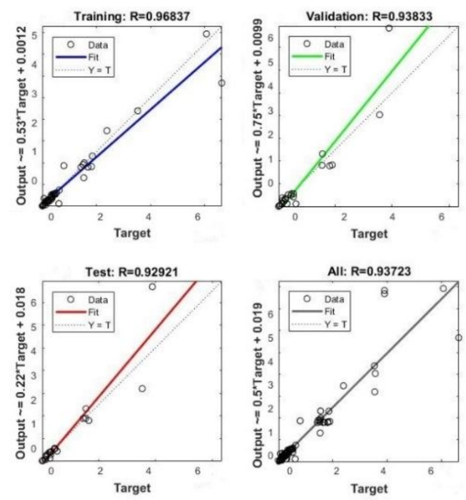



**Figure 9:** Results of Regression

The above figure shows the result of the training, validation, and testing data. The dashed line in each plot addresses the perfect correlation between the difference of result and outputs which leads to targets. The solid line addresses the best fit linear regression line among outputs and targets. The R value is a sign of the connection between the outputs and targets. If R = 1, this means that there's a linear relationship between outputs and targets. If R is on the brink of zero, then there's no linear relationship between outputs and targets. In this instance, the training data indicates an honest fit. The validation and test results also show R values that are greater than 0.9.

### 4.3 Error Autocorrelation

Fig. 10 demonstrates the results of error autocorrelation function. It determines how the forecast errors are interrelated in time. For a perfect forecast model, there must just be one non-zero value of the error autocorrelation function, and it should happen at zero lag. This implies that the forecast errors were entirely uncorrelated with one another. If there was substantial relationship in the forecast errors, then it would improve the forecast possibly by increasing the number of delays in the tapped delay lines. For the case, the error autocorrelation function falls roughly within the 100% confidence limits of zero, but only for the one at zero lag, so the model is satisfactory.

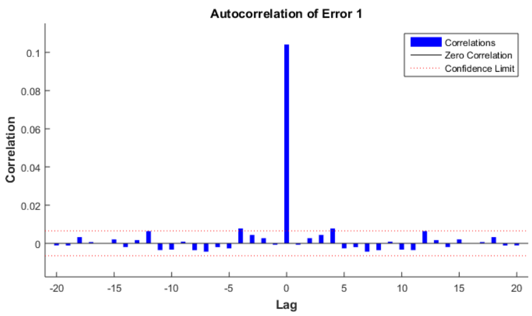



**Figure 10:** Results of Autocorrelation

### 4.4 Validation

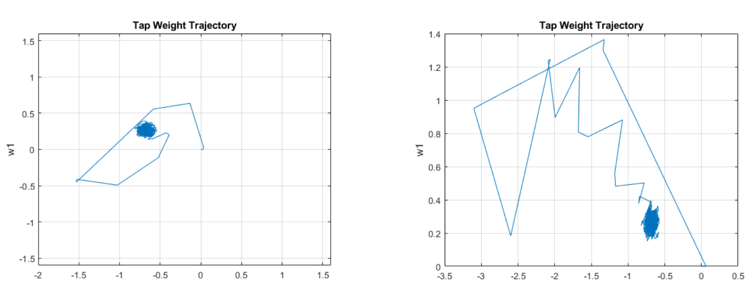
The proposed APFxLMS algorithm has been validated against Guo et. al. [24]. For this aim the following methods are applied.

i. Proposed APFxLMS
ii. FELMS algorithm by Guo et. al. [24]

Figure 14, 15, and Figure 16 show the results of

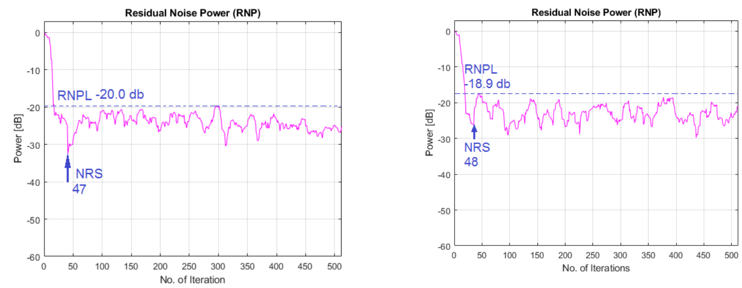
i. APFxLMS algorithm with α = -0.4 and μ = 0.04,
ii. FELMS algorithm with μ = -0.04

The parameter α and step size in the first case are determined so that the error should be small via trial and error approach. In the same way, step size and its sign are experimentally determined. However, in case of APFxLMS the step size μ = 0.04, while in case of FELMS if the step size μ = 0.04 is used it results in divergence. Therefore, the step size of FELMS algorithm must be reduced to μ = -0.04. The convergence speed of all these methods may appear in the tap weight trajectory in Fig. 11. These plots of the filter coefficients show the stability of the proposed algorithm. The algorithm of Guo takes much oscillating trajectory to converge, meanwhile the proposed system takes faster and relatively straight way to the optimal position. Finally, the proposed algorithm obtains lower finite residual noise power (RNP) lower than -20dB, on the other hand, Guo algorithm only attains -18.9 dB at the final update shown in Fig. 12. From these results it is observed that the algorithm Guo et al. have slow residual noise decreasing speed, whereas the proposed method in this study present reasonably fast convergence speed, which is generally the outcome in ANC.




(a) (b)

**Figure 11:** Tap Weight Trajectory, by (a) APFxLMS algorithm (α = -0.4 and μ = 0.04), (b) FELMS algorithm (μ = -0.04)




(a) (b)

**Figure 12:** RNP by (a) APFxLMS algorithm (α = -0.4 and μ = 0.04), (b) FELMS algorithm (μ = -0.04)

Table 2 shows the comparison of the proposed APFxLMS with ANCs in terms of Reduction Noise Power Level (RNPL) and Noise Reduction Speed (NRS) [12].

Table 2 Validation of the proposed APFxLMS

| | RNPL(db) | NRS |
|---|---|---|
| *APFxLMS* | -20.0 | 47 |
| *FELMS* | -18.9 | 48 |

## 5. CONCLUSION

There are a few noteworthy favorable circumstances related to the proposed methodology. Right off the bat, it gives a methodical strategy to ANC framework plan by a first-order all-pass filter reference LMS algorithm rather than estimation of the secondary path. The primary advantage to utilize the all-pass filter is that it changes the phase shift only while the magnitude of the response is not changing. It likewise does not need to execute Hilbert transform for changing over the algorithm into the frequency domain. Besides, it tends to be effectively executed progressively computerized separating activity. This gives a moderately straightforward approach to execute the technique in real time applications. The utilization of this examination set up an association with genuine issues. At last, a solitary parameter α can control stage an incentive for guaranteeing assembly conditions.

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