AN IMPROVED NARROWBAND ACTIVE NOISE CONTROL SYSTEM WITHOUT SECONDARY PATH MODELLING BASED ON THE TIME DOMAIN

Kuheli Mondal (Das)[1*], Saurav Das[2], Nozomu Hamada[3], Aminudin Bin Hj. Abu[4], Saikat Das[5], Waleed Fekry Faris[6], Hoong Thiam Toh[7], Akij Ahmad[8]

[1,4,7] Department of Mechanical Precision Engineering, Malaysia Japan International Institute of Technology, Universiti Teknologi Malaysia, KL, Malaysia.

[2] Department of Mechanical Engineering, St. Martin's Engineering college, Telangana, India.

[3] Department of System Design Engineering, Faculty of Science and Technology, Keio University, Yokohama, Japan.

[5] Department of Mechanical Engineering, Jadavpur University, Kolkata, India.

[6,8] International Islamic University Malaysia (IIUM), Gombak, Malaysia.

Abstract: Various kinds of ANC system are available including FxLMS with secondary path modelling to reduce acoustics noise. However, secondary path modelling causes the problems to increase the complexity of ANC implementation, reduction of performance caused by modelling error and requirement of auxiliary noise for secondary path modelling. The acoustic noise generated is further compounded by using secondary path identification which makes the system complex. Therefore, several approaches have been proposed for modifying the FxLMS to solve these problems. There are several available ANC algorithms that do not require secondary path estimation. However, some have drawbacks, such as slow convergent speed, the complexity of the phase shift mechanism. To solve these problems, a novel approach with no secondary path modelling is adopted, in which the adaptation stability is guaranteed by switching the sign of the step size. It is combined with the on-line tunable delay of the reference signal to significantly improve the adaptation convergence properties of the algorithm. The present study investigates the acoustic noise by the ANC system without secondary path identification. This study gives an insight into the robustness of the proposed ANC system that can annul the engine noise and can increase passenger comfortability. A new mathematical modelling has been proposed to reduce the acoustic noise that increases the convergence criteria.

Keywords: ANC, Delay LMS, Secondary Path Modelling, Time Domain, All-Pass Filtered x LMS.

Reference to this paper should be made as follows: Mondal (Das), K., Das, S., Hamada, N., Abu, A. B. H., Das, S., Faris, W. F., Toh, H. T., Ahmad, A., (2019) 'An Improved Narrowband Active Noise Control System without Secondary Path Modelling based on the Time Domain', International Journal of Vehicle Noise and Vibration.

Biographical notes: Kuheli Mondal (Das) is a Doctoral research student in the Department of Mechanical Precision Engineering, Malaysia Japan International Institute of Technology, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia. Her current research is to develop a novel robust and accurate narrowband feedforward ANC using All-Pass FxLMS (APFxLMS) algorithm for vehicles noise. Her research interest is signal processing and noise control.

Assoc. Prof. Dr.Saurav Das is the Head of the research group in Department of Mechanical Engineering, St. Martin's Engineering college, Telangana, India. His research area includes fluid structural interactions, where novel mathematical modelling has been adopted to study the complex physics. He is also working acoustic noise control of automobiles, pertaining to exhaust noise of muffler.

Professor Dr Nozomu Hamada is a signal processing researcher. He is a Professor Emeritus of Keio University where he was a professor in the System Design Engineering, Faculty of Science and Technology, Keio University, Yokohama, Japan. From 2013 to 2016, he was a Professor in the Electronic System Engineering at Malaysia-Japan International Institute of Technology (MJIIT), University Technology Malaysia (UTM). His research interests include circuit theory, stability theory of dynamical systems, digital signal processing, and image processing. His recent research field is the realization of a human interface system using microphone arrays.

Assoc. Prof. Dr. Aminudin Bin Hj Abu is the Head of IDS ikohza. He completed his Dip. Eng (SNPU, Seoul, Korea), B.Eng (Hanyang Univ., Seoul, Korea), M.Sc in Mechanical Precision Eng (Hanyang Univ. Seoul, Korea), Dr. Engineering in Automotive Eng. (Hanyang Univ. Seoul, Korea).He has won numerous awards and has numerous publications. His Research interests are a) Noise and Vibration, b) Damage Detection and Fatigue c) Model Updating, d) Sensitivity Analysis, e) Design of Experiment.

Saikat Das is a Research Assistant (Research Scholar) in the Heat Power Laboratory under the Department of Mechanical Engineering, Jadavpur University, Kolkata, India. His research interests include Computational Fluid Dynamics (CFD), High speed compressible flows (Supersonic Flows), Finite Difference Methods, Finite Volume Methods, Finite Element Methods, Turbulence analysis in supersonic flows, Development of High-Fidelity solvers, Discrete Element Method, Space time Conservation Element (CESE) Method, Mechanics of Composites in Aerostructures, Development of Finite Element codes for analyzing various mechanics of composite laminates and pre-twisted composite conical shells.

Professor Dr. Waleed Fekry Faris is a Professor in the Department of Mechanical Engineering, International Islamic University Malaysia (IIUM). He got his BSc and MSc in Mechanical Engineering from Zagazig University, Egypt. His Ph.D. in non-linear systems was from Virginia Tech, USA. Prof. Faris is a well-known internationally in the fields of dynamics and control and vehicle dynamics.

Dr. Toh Hoong Thiam is a Senior Lecturer. He completed his B.Eng (NUS, Singapore), M.Sc in Mechanics and Processing of Materials (NTU, Singapore), M.S Aerospace Engineering (MSU, USA), Ph.D. Engineering Mechanics (Virginia Tech, USA). He has numerous publications. His research interests are a)Computational Fluid Dynamics, b)Finite Element Analysis, c)Wave Propagation in Fluid and Solid Media, d)Fluid- Structure Interaction Problems.

Akij Ahmad is a master research student in the Department of Mechatronics Engineering of International Islamic University Malaysia (IIUM), Gombak, Malaysia. His current research is to develop a roll mechanism of FWMAV and his interest lies in the automobile, software, avionics, and UAV.

1 Introduction

ANC systems in automobiles have evolved rapidly over the last decades. The new generation of auto-engines has led to the increment of engine power leading to more importance of noise reduction. This can be achieved by incorporating the ANC controller for lowering automobile noise and enhancing customer comfortability. In this regard, there is an urgent need for the development of ANC controllers that can be robust and accurate. Various kinds of ANC system are available including FxLMS with secondary path modelling. However, secondary path modelling leads to an increase of the complexity of ANC implementation, reduction of performance caused by modelling error and requirement of auxiliary noise for secondary path modelling. Several approaches have been proposed for modifying the FxLMS to solve these underlying problems. Qatu et. al. (2009) presented an overview of automotive vehicle noise, vibration, and harshness (NVH) engineering. It classified the interior noise into powertrain-related NVH, road- and tyre-related NVH and wind-related NVH. This paper also discussed brake and chassis-related NVH, squeak, and rattle and electromechanical-related NVH. They (2012) also presented a summary of recent research in the general area of Vehicle noise, vibration and harshness (NVH) with an emphasis in the automotive field. It follows up on a previous review and classifies the phenomena by the main sources of NVH into powertrain, road and tyre, wind and other NVH. The paper provided a review of some of the recent literature in this field.

Currently, several ANC systems without secondary path modelling have been developed, but some have drawbacks, such as slow convergent speed and complexity of the phase shift mechanism. This study addresses the design of a novel single channel narrow band feedforward ANC controller which improves the two drawbacks mentioned above. The proposed ANC system should realize phase shifter in simpler configuration or digital signal processing devise so that the adaptation will perform in real time and ensure the convergence of the LMS algorithm. The main benefit of using an all-pass filter is that it changes the phase shift only while the magnitude of the response is not changed. The proposed system does not need to transform into the frequency domain as performed in previous algorithms (Wu et. al., 2008). It also does not require a Hilbert transform for converting the algorithm into the frequency domain. The proposed ANC can be implemented for reducing noise in the air intake duct system, and hence it will improve the passenger comfortability. The acoustic noise generated is further compounded using secondary path identification which makes the system complex. The present study investigates the acoustic noise by the ANC system without secondary path identification. A new mathematical modelling has been proposed to reduce the acoustic noise that increases the convergence criteria. The objective of this paper is to develop an improved narrowband Active Noise Control system without secondary path modelling based on the time domain using a 1st order all-pass filtered x LMS algorithm and this proposed system is verified and compared with a standard and recent benchmark problem. The acoustic noise generated is further compounded using secondary path identification which makes the system complex

2 Theory

2.1 ANC without secondary path modelling

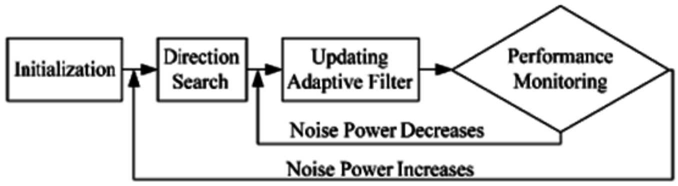
As discussed previously in the introduction section, the secondary path in ANC system plays an important role because the convergence condition of adaptive filtering is closely related to the estimation error of the secondary path response and the real secondary path response varies with time. The most popular online identification method of the secondary path transfer function is to inject an additional modeling noise into the loudspeaker. This additional noise contributes to the residual noise and this identification parts increase the control system complexity.

To avoid these problems, there are some ANC algorithms that do not require a secondary path system. Some of them called direction search LMS algorithm and discussed below, update the direction of adaptive filter by monitoring the residual error.

2.1.1 Zhou's Standard LMS Approach

A single-tone noise ANC (Zhou et. al., 2007) does not require the identification of the secondary path transfer function. Their developed method is simple to implement, yields good performance, and converges quickly compared to other available control algorithms that do not require secondary path identification. In Fig. 1, the structure of their algorithm is shown, and it is divided into four stages, i.e., initialization, direction search, updating, and performance monitoring.

Figure 1 Four Steps of Direction Search Algorithm (Zhou et. al., 2007)



Four stage Algorithm

The steps of Zhou's approach for changing the step size sign is shown in Fig. 1 is as follows:

i. Initialization: Initialize the adaptive filter weights and a sufficiently small the step size
ii. Direction Search: Without updating the filter weights, monitor the error power. If the error power increase, then change the sign in front of μ.
iii. Updating: Update the adaptive filter weights
iv. Performance Monitoring: Compute the mean noise power and mean reference noise power, then determine whether to keep updating or to do the direction search

2.1.2 Other's Approach

The ANC algorithm (Wu et. al., 2008) was improved for single-tone noise cancellation without secondary path identification. To realize four directions updating to 180^0, 0^0, and $+/-90^0$ frequency-domain delay-less sub band representation of reference, as well as an error signal, is introduced. The LMS algorithm is adopted in the frequency domain. This method tries to test these four update step size directions and select the one that achieves best cancellation result. The obtained results show that it yields better performance and faster convergence than Zhou's algorithm.

There are some other approaches which have been discussed here briefly. A hybrid active noise cancelling (HANC) algorithm (Caudana et. al., 2008) was proposed to overcome the acoustic feedback present in most ANC system, together with an efficient secondary path estimation scheme. Many different adaptive control algorithms were implemented in the recently developed remotely controlled Virtual Instrument Systems in Reality (VISIR) ANC/DSP (Moazzam et. al., 2013) remote laboratory to evaluate the performance of adaptive algorithms. Based on the strict positive real property of the FxLMS algorithm phase shifter (Zhang et. al., 2010) was introduced to an ANC, where Hilbert transform filter is used for phase compensation. An adaptive algorithm based on neural networks was proposed for nonlinear ANC systems (Zhang et. al., 2010), with no secondary path modelling by introducing virtual primary noises to modify the ANC structure. Their controller utilizes neural networks to attenuate the effect of the primary noises and it also has a simpler structure and less computation complexity. An approach with no secondary path modelling was proposed (Kurczyk et. al., 2014), in which the adaptation stability is guaranteed by switching the sign of the step size. They also used a fuzzy inference system (Kurczyk et. al., 2014) to evaluate both sign and magnitude of the step size.

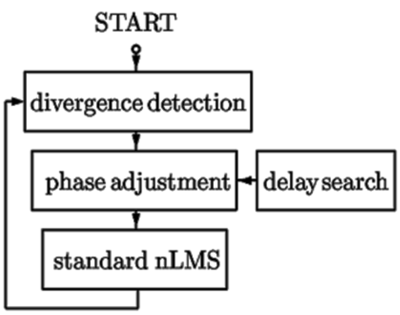
2.1.3 Delay LMS

An approach with no secondary path modeling (Kurczyk et. al., 2014), which was also proposed (Kajikawa et. al., 2000 and Kajikawa et. al., 2003) in which the adaptation stability is guaranteed by switching the sign of the step size. It is combined with the on-line tunable delay of the reference signal to significantly improve the adaptation convergence properties of the algorithm.

The algorithm consists of the following two main stages shown in Fig. 2:

i. Phase Adjustment: Estimate the energy of error while ANC is off, the following four directions are evaluated when normalized LMS (nLMS) adopted: μ is positive and $k(n) = 0$, μ is negative and $k(n) = 0$, μ is positive and $k(n) > 0$, μ is negative and $k(n) > 0$.
ii. Divergence Detection: For estimated error energy, if the estimated energy increases over an assigned threshold, then the algorithm returns to the Phase adjustment stage.

Figure 2 Algorithm structure (Kurczyk et. al., 2014)

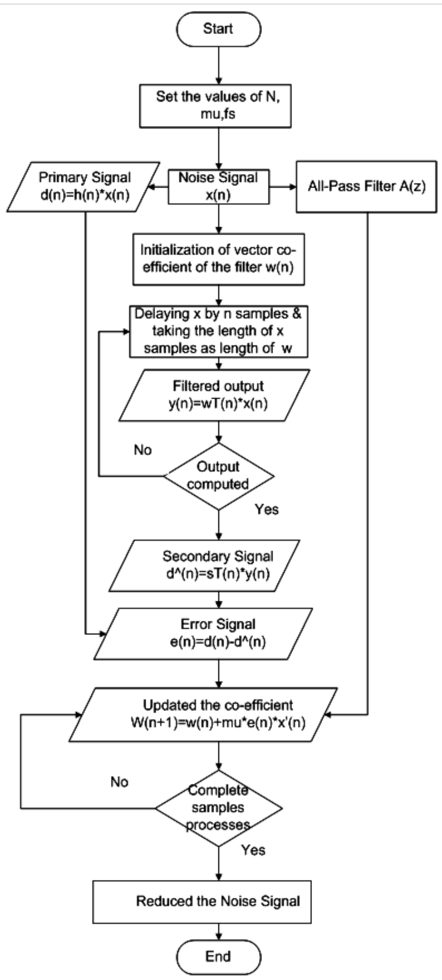


3 Methods

3.1 The flow of ANC using APFxLMS

The Fig. 3 illustrates the complete flow chart of ANC without secondary path modelling using All-Pass Filtered x LMS. From the flowchart, the two-main part i.e. primary and secondary sources are used to minimize the noise signal. Initially, the values of samples of the filter (length), step-size and sampling frequency which are the most important parameter of the adaptive filter are setups. The step-size of the filter should be greater than zero but less than one-half of the maximum value of reference signal samples from literature. The weight of the filter is initialised whose length is dependent on the length of the filter, i.e. the length of the weight vector is same as the length of the filter; initially, the weights are assigned to zero. In order to compute the output of the filter, some samples of the reference signal have to be multiplied with the weight vector, hence in order to multiply reference samples with weight vector, the matrix size of the sample of reference signal should be the same as the weight vector, but either one should be row vector, and another should be column and hence number of reference samples is taken the same as of weight vector. After obtaining filter output, secondary signal is measured and after that error signal is computed, by subtracting the output samples of the secondary source from primary signal samples. The weight value of the filter is updated with the help of the all-pass filter. These three processes are considered in a loop, so that error (e) and (y) are computed for all the samples.

Figure 3 Flow Chart of ANC without secondary path modelling using All-Pass Filtered x LMS

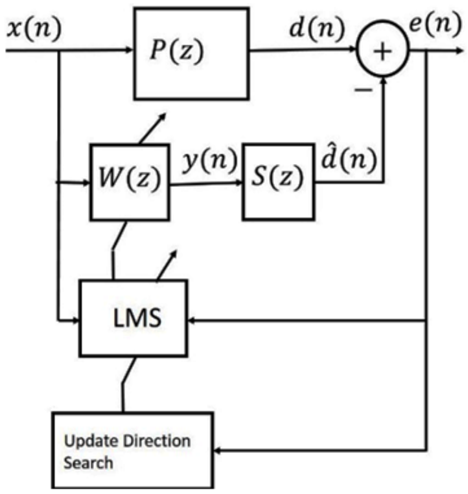


3.2 Convergence Analysis of ANC without secondary path identification

In this section, the convergence analysis of the direction search LMS approaches is described. The discussion here is restricted within the ANC system for narrowband noise cancellation.

Fig. 4 illustrates a block diagram of ANC without secondary path identification based on the direction search LMS algorithm (Qiu et. al., 2014 and Gao et.al., 2016). Unlike the FxLMS, the reference signal $x(n)$ is directly used for adaptive control without pre-filtering of an estimated secondary path transfer function. The most important part is the update direction search portion in this configuration, and some approaches were proposed.

Figure 4 Direction Search LMS Algorithm (Zhou et. al., 2007)



For ANC without estimated secondary path as shown in Fig. 4, the update of the adaptive filter coefficients $w(n)$ based on the LMS algorithm is written as

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

where μ is a sufficiently small step size. One can see that in Equation 1, the reference signal does not need to pass through the secondary path. According to [3], for a signal-tone input $X_\omega(n)$ with angular frequency ω,

$$W_\omega(n) = W_\omega(n-1) + \mu P_x(\omega)|s_\omega|[\frac{P_\omega}{S_\omega} - W_\omega(n-1)]e^{j\angle s_\omega} \tag{2}$$

where $\angle S_\omega$ represents the angle of $S_\omega$and $|S_\omega|$ represents the amplitude of S_ω.

Thus, the conditions of the LMS algorithm can converge if it satisfies the below mentioned Equation 3 and Equation 4.

$$\mu < \frac{2\cos\angle S_\omega}{P_x(\omega)|S_\omega|}, \tag{3}$$

$$|\angle S_\omega| < 90^\circ . \tag{4}$$

Consequently, the update of $W_\omega(n)$ converges to the ideal value even without secondary path identification. On the other hand, if $|\angle S_\omega| > 90^\circ$, then the adaptive update algorithm will fail to convergence so that the ANC could not cancel the reference noise. To avoid this divergence, the sign in front of the step size in Equation 1 is changed, as shown below,

$$\boldsymbol{w}(n) = \boldsymbol{w}(n-1) - \mu e(n)\boldsymbol{x}(n) \tag{5}$$

Then, it becomes like as in Equation (2)

$$W_\omega(n) \approx W_\omega(n-1) + \mu P(\omega)|S_\omega|\left[\frac{P_\omega}{S_\omega} - W_\omega(n-1)\right]e^{j(\angle S_\omega - 180^\circ)} \tag{6}$$

The convergence condition of Equation 6 in this updating formula is given by $|\angle S_\omega - 180^\circ| < 90^\circ$, and this condition is satisfied for the current case $|\angle S_\omega| > 90^\circ$. The next problem is to know when to change the sign of step size to give a converging adaptive filter weight update.

In the frequency domain at the angular frequency ω of the reference signal $x(n)$, the block wise updating scheme of adaptive filter weight vector is given as:

$$W(\omega, k+N) = W(\omega, k) - \mu C(k) X_\omega(k) E_\omega(k) \tag{7}$$

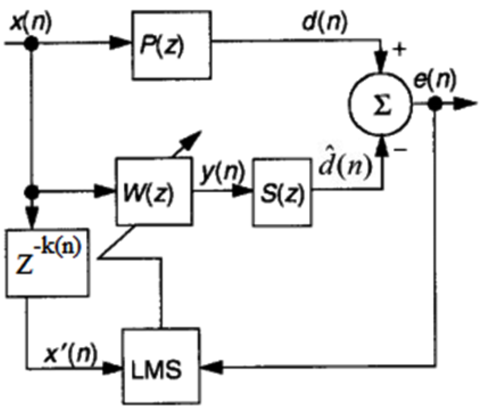
where N is the length of block or FFT length, k is the time index of a block, $C(n)$ is assumed to be $+1, -1, +i, or -i$, (i: imaginary unit), and $X_\omega(n)$ and $E_\omega(n)$ are the frequency components of $x(n)$ and $e(n)$ at the frequency ω.

The update direction $C(n)$ is given by the angle of $+1, -1, +i, or - i$, that is, 0°, 180°, and $\pm 90^\circ$. Basically, the algorithm by Wu's ANC has the same scheme as the block diagram shown in Fig. 7. The merit of using either $+i, or - i$ is to avoid slow convergence when the response of the secondary path is close to $\pm 90^\circ$. In addition to the direction, $C(n)$ can also control the step size. However, Wu' LMS has carried out in block wise FFT domain, so that some time delay is introduced at weight updating computation by computational complexity caused by the sub band splitting. However, the above discussed ANC without secondary path identification is operated in the frequency domain. This previous approach, therefore, required Hilbert transform for converting the algorithm into the frequency domain. The main benefit to using all-pass filter is that it changes the phase shift only while magnitude of the response does not change. The proposed system does not need to transform into frequency domain as performed in previous algorithms (Wu et. al., 2008). It also does not need to implement a Hilbert transform for converting the algorithm into the frequency domain.

3.3 Delay LMS

The idea of the delayed LMS algorithm was extended (Kurczyk et. al., 2014) where instead of an estimated secondary path model, time delay operator with variable delay time is used. Fig. 5 illustrates the block diagram of the delay variable LMS algorithm.

Figure 5 ANC with the shifted-delay LMS algorithm (Kurczyk et. al., 2014)



The delay variable $k(n)$ is an integer which can control direction search and it is tuned in conjunction with the step size change. The filter weight update equation, called varying-delay LMS algorithm with normalization step size is given by

$$\boldsymbol{w}(n) = \boldsymbol{w}(n-1) - \frac{\pm\mu_N}{\|r(n)\|^2} e(n)\boldsymbol{x}(n-k(n)) \tag{8}$$

where μ_N is normalized step size defined by the user, and $r(n)$ is the output of delay operator.

This adaptation algorithm repeats the following two stages:

Phase adjustment – Selecting the parameters (μ and k) that improve the convergence speed by testing four sets. 1) μ is positive, and k=0; 2) μ is negative, and k=0; 3) μ is positive, and k>0; 4) μ is negative, and k>0;

Divergence direction – Estimate the error signal energy, if it is over the predefined threshold, then the algorithm returns to the phase adjustment stage.

In the phase adjustment stage, two cases with k=0 are the same adaptation processes used in Zhou's ANC system.

In the tonal noise reduction which is addressed in this research, the delay integer k can be defined as the following form [5]

$$k = round\left(\frac{f_s}{4f}\right) \tag{9}$$

where f stands for signal frequency, f_s is the sampling frequency, and round means the rounding to the nearest integer.

3.4 APFxLMS

The proposed ANC insert all-pass filter by replacing the estimated secondary path transfer function. The all-pass filter is an IIR (Infinite Impulse Response) filter whose magnitude response is constant over its entire frequency, but its phase response is variable. From these properties, the all-pass filter can be designed so that its phase response compensates the nonlinear phase response of the overall system. In this context, the all-pass filter is sometimes called a phase shifter or equalizer. The following transfer function describes a first order all-pass filter:

$$A(z) = \frac{z^{-1}-\alpha}{1-\alpha z^{-1}} \tag{10}$$

where the numerator polynomial coefficients are $(1, -\alpha)$ and the denominator polynomial coefficients are $(-\alpha, 1)$, and α is a real number satisfying $|\alpha| < 1$ for stability reason. The frequency response of $A(z)$, its amplitude response, and phase response are given by the following equations:

$$A(e^{j\omega}) = \frac{e^{-j\Omega}-\alpha}{1-\alpha e^{-j\Omega}} \tag{11}$$

$$|A(e^{j\Omega})| = \left|\frac{e^{-j\Omega}-\alpha}{1-\alpha e^{-j\Omega}}\right| = 1 \tag{12}$$

$$\angle A(e^{j\Omega}) = \angle e^{-j\Omega}\frac{1-\alpha e^{j\Omega}}{1-\alpha e^{-j\Omega}} = e^{-j\Omega} - 2\tan^{-1}\frac{\alpha\sin\Omega}{1-\alpha\cos\Omega} \tag{13}$$

where $\Omega \in (-\pi, \pi)$ is the normalized frequency in the discrete-time domain, which is related with analog angular frequency $\omega = 2\pi f$ (f [Hz]) as:

$$\Omega = \frac{\omega}{f_s}, \qquad (f_s\text{: Sampling frequency}) \tag{14}$$

The phase shift value at a specific frequency Ω is controlled by varying the parameter α over $(-1,1)$. In fact, when we set the angular frequency of a single tone noise as $\omega = 2\pi f$ the phase shift of the all-pass filter of Equation 11 is given by:

$$\angle A(e^{j\Omega}) \quad \text{at} \quad \Omega = \frac{2\pi}{f_s}$$

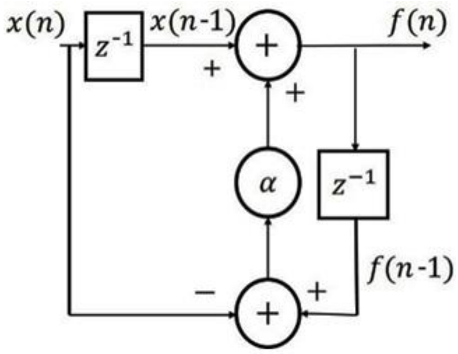
For example, if the reference noise with frequency is 100 Hz ($\omega = 2\pi \cdot 100$) and the sampling frequency is 400Hz, then from Equation 7 $\Omega = \frac{200\pi}{400} = \frac{\pi}{2}$. By substituting $\Omega = \frac{\pi}{2}$

into Equation 6, the relationship between the phase shift at $\Omega = \frac{\pi}{2}$ and α is given by

$$\angle A\left(e^{j\frac{\pi}{2}}\right) = -\frac{\pi}{2} - 2\tan^{-1}\alpha \tag{15}$$

The block $A(z)$ is realized by the block diagram according to the transfer function of the 1st order all-pass filter as described in Equation 10 in Fig. 6.

Figure 6 Block Diagram of all-pass Filter

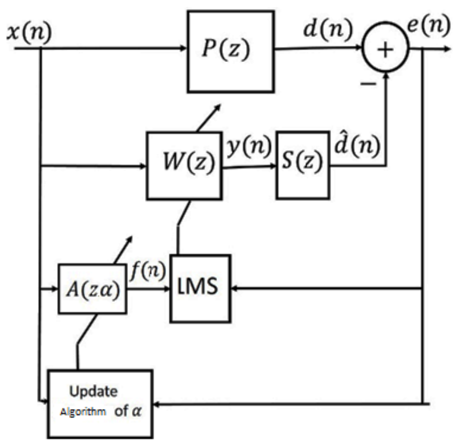


From Fig. 6, the filtered output signal $f(n)$ is generated by the following difference equation:

$$f(n) = \alpha f(n-1) - \alpha x(n) + x(n-1) = \alpha\{f(n-1) - x(n)\} + x(n-1) \tag{16}$$

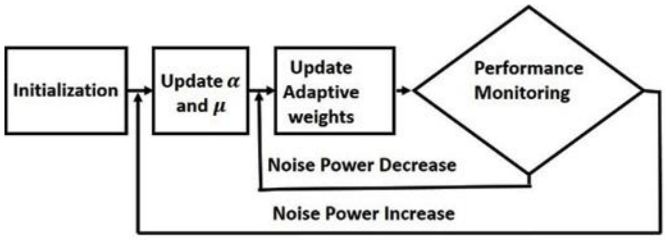
The block diagram of the proposed all-pass filtered x LMS (APFxLMS) is shown in Fig. 7. In the figure, (Modal(Das) et. al., 2018) the block of $A(z,\alpha)$ is realized by the block diagram as shown in Fig. 6, where the parameter α will be controlled by monitoring error behavior.

Figure 7 All pass-filtered x LMS without secondary path modelling



The function of the updating parameter α and the step size is divided into four stages as shown in Fig. 8. Basically, the updating algorithm (Wu et. al., 2008, Zhou et. al., 2007and Kurczyk et. al., 2014) is the same as the proposed one.

Figure 8 Updating schemes of filter weights, step size, and parameter α



In the frequency domain, the transfer functions $P(z), S(z), A(z)$, and $W(z)$ are represented by the complex numbers of $P_\Omega \triangleq P(e^{j\Omega}), S_\Omega \triangleq S(e^{j\Omega}), A_\Omega \triangleq A(e^{j\Omega})$, and $W_\Omega \triangleq W(e^{j\Omega})$. Since the complex numbers of S_Ω and A_Ω can are represented by their polar form as:

$$S_\Omega = |S_\Omega| e^{j\theta_S}, \quad A_\Omega = e^{j\theta_A(\alpha)} \tag{17}$$

where $\theta_S = \angle S(e^{j\Omega})$, and $\theta_A(\alpha) = \angle A(e^{j\Omega})$, the following expression, which is an equivalent form of Equation 10, is obtained in the next equation.

$$\frac{A_\Omega}{S_\Omega} = \frac{1}{|S_\Omega|} e^{j(\theta_A(\alpha) - \theta_S)} \tag{18}$$

Substituting $c_\omega = \frac{1}{|S_\Omega|}$, $\theta_\omega = \theta_A(\alpha) - \theta_S$ into the convergence conditions Equation 3 and Equation 4 yields the convergence conditions of APFxLMS as in the following equations.

$$\mu < \frac{2\cos(\theta_A(\alpha) - \theta_S)}{P_x(\Omega)|S_\Omega|}, \tag{19}$$

$$|\theta_A(\alpha) - \theta_S| < \pi/2 \tag{20}$$

where $P_x(\Omega)$ is the power spectrum of the reference noise $x(n)$. If the step size μ is set as a sufficiently small value, the condition in Equation 12 can be satisfied. On the other hand, if the phase of the secondary path system θ_S is negative, a proper parameter α can be chosen so that $\theta_A(\alpha)$ becomes θ_S as close as possible.

4 Simulation Results

To show the effectiveness of the proposed APFxLMS algorithm, several computer simulation experiments are conducted the same as of (Zhou et. al., 2007). The ANC systems designed for this purpose are summarized as follows.

Primary System: FIR filter model with impulse response shown as

$h(n) = \delta(n-3) - 2.70833\delta(n-4) + 4.18611\delta(n-5) - 3.0451\delta(n-6) + 0.730071\delta(n-7)$ (21)

Secondary Path: the secondary path is modelled by an IIR filter with the following transfer function as shown

$$S(z) = \frac{1+0.96z^{-1}+0.4923z^{-2}}{1+1.06z^{-1}+0.3352z^{-2}} \quad (22)$$

Adaptive Filter: A transversal filtering operation is used to produce an adaptive filtering output signal and an adaptation algorithm is used to adjust the coefficients of the filter. The most widely used technique for ANC systems using a transversal filter such as FIR filter and the rate of convergence should be enhanced by LMS or Filtered x LMS algorithm. There are following two reasons for applying the first order adaptive filter for simulation.

i. As shown in Zhou and DeBrunner [2], the first order LMS filter is sufficient for stable control by appropriately chosen size and the sign of μ.

ii. The convergent profile of the weight updating can be observed as their step-by-step trajectory in w_0-w_1 plane. In this simulation, the first order FIR adaptive filter is represented by

$$y(n) = w_0(n)x(n) + w_1(n)x(n-1) \quad (23)$$

Performance Evaluation: The performance of the proposed algorithm as well as conventional methods are evaluated in terms of residual noise power or normalized residual noise power is defined as follows:

Residual Noise Power (RNP) = $10\log_{10} E[e^2(n)]$ (24)

Normalized Residual Noise Power (NRNP) = $10\log_{10}\frac{E[e^2(n)]}{E[d^2(n)]}$ (25)

Here several simulations will be conducted for a sinusoidal reference signal of 120Hz. Assuming the sampling frequency of 800Hz means that the normalized discrete time frequency of the reference signal is $\Omega = 2\pi * 120/800 = 0.3\pi$. The input reference sinusoidal signal $x(n)$ can be represented as $x(n) = A\sin 0.3\pi n$, where *A*, is the amplitude of the input signal.

4.1 APFxLMS Algorithm

The proposed APFxLMS system is realized by the best value α. At first, the best α is chosen from the four cases where each α realizes one of the phase shift of all-pass filter by amounts of $\angle A(e^{j\Omega}) = -\frac{\pi}{4}, -\frac{\pi}{2}, -\frac{3\pi}{4}, -\pi$ and these cases are demonstrated as follows:

Case 1: $\alpha = -0.4$, which $\angle A(e^{j\Omega}) \approx -\frac{\pi}{4}$ is realized by $\mu = 0.04$

Case 2: $\alpha = 0$, which $\angle A(e^{j\Omega}) \approx -\frac{\pi}{2}$ is realized by $\mu = 0.03$

Case 3: $\alpha = 0.4$, which $\angle A(e^{j\Omega}) \approx -\frac{3\pi}{4}$ is realized by $\mu = -0.04$

Case 4: $\alpha = 1.0$, which $\angle A(e^{j\Omega}) \approx -\pi$ is realized by $\mu = -0.03$

Fig. 9 shows the results of APFxLMS algorithm without secondary path modelling. From Fig. 9 (a), it is clearly observed that the primary signal with the noise signal is completely superimposed by the secondary signal. The updated trajectory of adaptive filter weights $w_0(n), w_1(n)$ in the two-dimensional plane is shown in Fig. 9 (b). The initial weight vector is the origin (0, 0), and the updating weights converge to an optimal weight vector around (-0.75, -0.5). Fig. 9 (b) shows the condition of the convergence, which shows that the system converges in a much smoother way. The Fig. 9 (c) shows the faster decreasing profile of the residual noise power (RNP) at each weight iteration and it can be noticed that the stability of the system become steady faster.

Comparing the results of these four cases reveals that fast adaptation speed is realized in the cases of $\alpha = -0.4$ and $\alpha = 0.0$. The process to find appropriate α for faster adaptation speed is continued. From Figure 9 to Figure 11, it is clearly observed that the proposed APFxLMS get a better result other than Standard LMS and Delay LMS. However, as the values of α and μ is increased, it is noticed that the noise cancellation effect is deteriorating (refer Fig. 12).

Case 1:

Figure 9 Results of APFxLMS algorithm ($\alpha = -0.4, \mu = 0.04$), (a) Noise, Primary, Secondary and Residual noise signal (b) Tap Weight Trajectory, (c) RNP

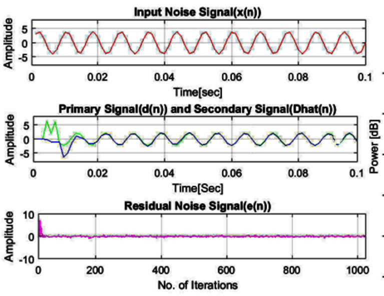


Figure 9(a)

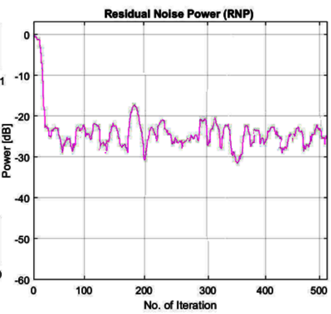


Figure 9(c)

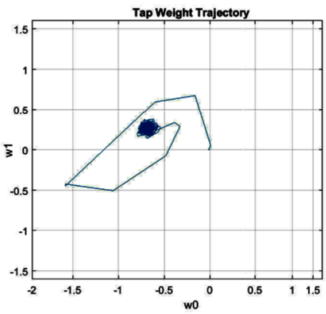


Figure 9(b)

Case 2:

Figure 10 Results of APFxLMS algorithm ($\alpha = 0, \mu = 0.03$), (a) Noise, Primary, Secondary and Residual noise signal, (b) Tap Weight Trajectory, (c) RNP

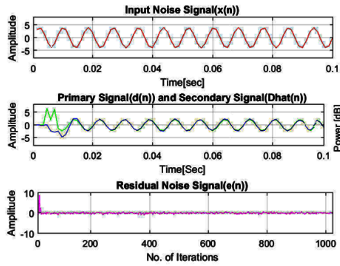


Figure 10(a)

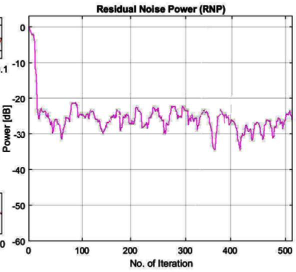


Figure 10(c)

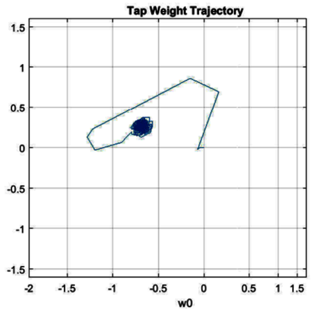


Figure 10(b)

Case 3:

Figure 11 Results of APFxLMS algorithm ($\alpha = 0.4, \mu = -0.04$), (a) Noise, Primary, Secondary and Residual noise signal, (b) Tap Weight Trajectory, (c) RNP

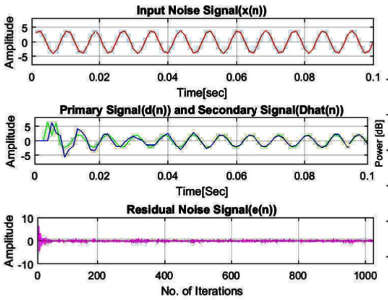


Figure 11(a)

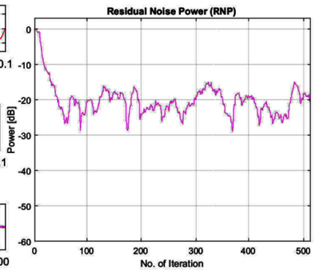


Figure 11(c)

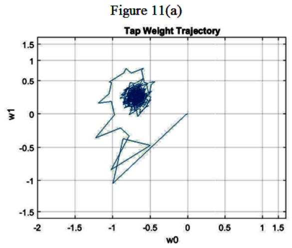


Figure 11(b)

Case 4:

Figure 12 Results of APFxLMS algorithm ($\alpha = 1.0, \mu = -0.03$), (a) Noise, Primary, Secondary and Residual noise signal, (b) Tap Weight Trajectory, (c) RNP

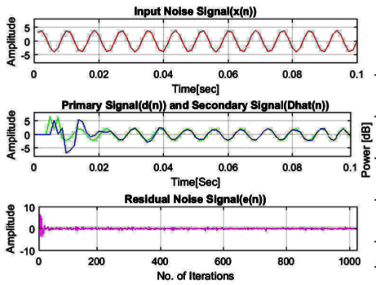


Figure 12(a)

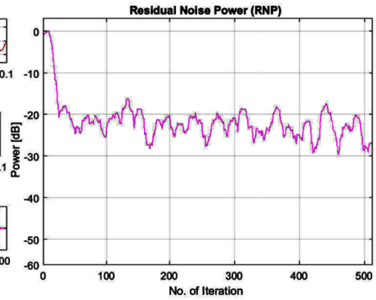


Figure 12(c)

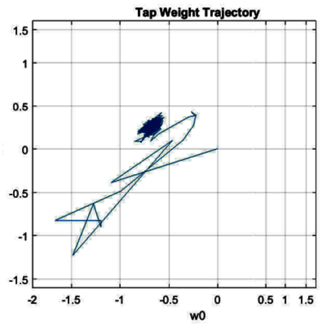
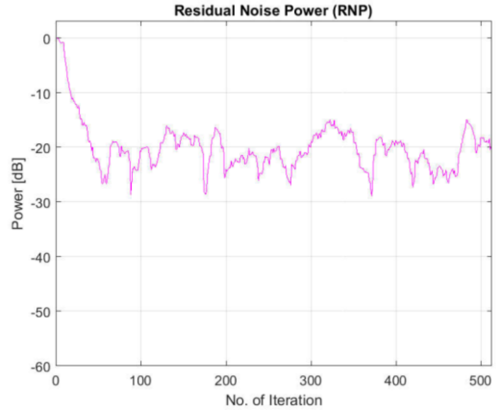
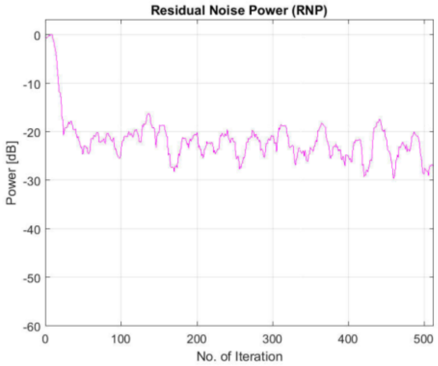
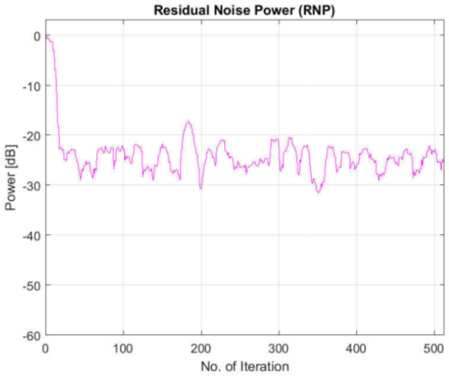


Figure (b)

4.1.1 Appropriate values of μ

Table 1 summarizes the simulation results of APFxLMS for several μ's and α's which varies from -0.04 to 0.04 and -0.4 to 1 respectively, to find faster convergence speed than the system. From the results, the appropriate value of μ is equal to 0.04 and α is equal to -0.4which provide the fastest adaptation speed is observed.

Table 1 RNP for suitable values of μ

	RNP		RNP
μ -0.04		μ 0.03	
α 0.4		α 0	
μ -0.03		μ 0.04	
α 1		α -0.4	

4.2 Performance evaluation

For evaluating the noise reduction ability of each algorithm, the following two performance indexes are introduced.

Reduction Noise Power Level [dB] (RNPL): This value is defined by the maximum power level for the steady-state time interval for evaluating noise suppression ability of the adaptation mechanism.

Noise Reduction Speed (NRS): In the simulations treated in this thesis, the NRS is defined as the first iteration step at which the RNP crosses down the -20dB level. This value indicates the convergent speed of adaptation mechanism. These two performance indexes are obtained and shown in Fig. 13. From Fig. 13, it observed that RNPL and NRS of Standard LMS and Delay LMS are -12.4dB, -15.3 dB and 44, 18 respectively, whereas RNPL and NRS of the proposed APFxLMS are -20.2 dB and 17, which reach the best result among all ANCs.

Figure 13 RNPL and NRS results for (a) Standard LMS ($\mu = 0.04$) (b) Proposed APFxLMS ($\alpha = -0.4, \mu = 0.04$) (c) Delay LMS ($\mu = -0.04$)

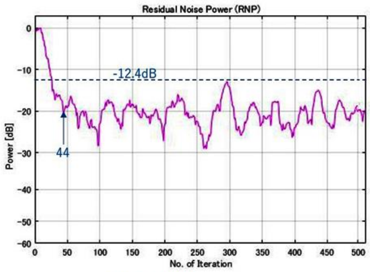


Figure 13(a)

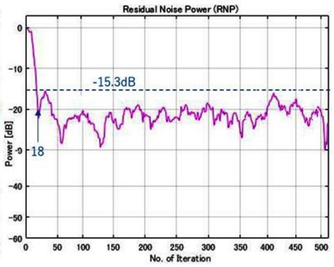


Figure 13(c)

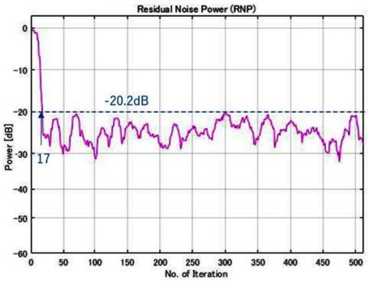


Figure 13(b)

However, in the case of Standard LMS and APFxLMS the step size $\mu = 0.04$, while in case of Delay LMS if the step size $\mu = 0.04$ is used it results in divergence. Therefore, the step size of Delay LMS must be reduced to $\mu = -0.04$.

The convergence speed of ANC methods may appear in the tap weight trajectory in Fig. 14 (a), (b), and (c). These plots of the filter coefficients show the stability of the proposed algorithms. Comparing the tap weight trajectory of all algorithms, the proposed system takes a faster and relatively straight way to the optimal position.

Figure 14 Tap Weight Trajectory for (a) Standard LMS ($\mu = 0.04$) (b) Proposed APFxLMS ($\alpha = -0.4, \mu = 0.04$) (c) Delay LMS ($\mu = -0.04$)

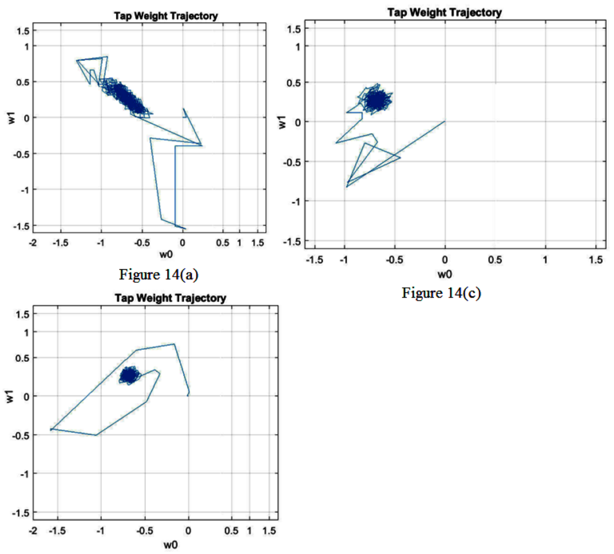


Figure 14(a) Figure 14(b) Figure 14(c)

Comparing the results shown in Fig. 15 (a), (b) and (c) shows that the Standard LMS and Delay LMS algorithms have slow residual noise decreasing speed, whereas the proposed method in this study presents quite fast convergence speed, which is generally wanted in ANC. Table 2 shows the comparison of the proposed APFxLMS with ANCs in terms of RNPL and NRS.

Figure 15 Residual noise signal for (a) Standard LMS ($\mu = 0.04$) (b) Proposed APFxLMS ($\alpha = -0.4, \mu = 0.04$) (c) Delay LMS ($\mu = -0.04$)

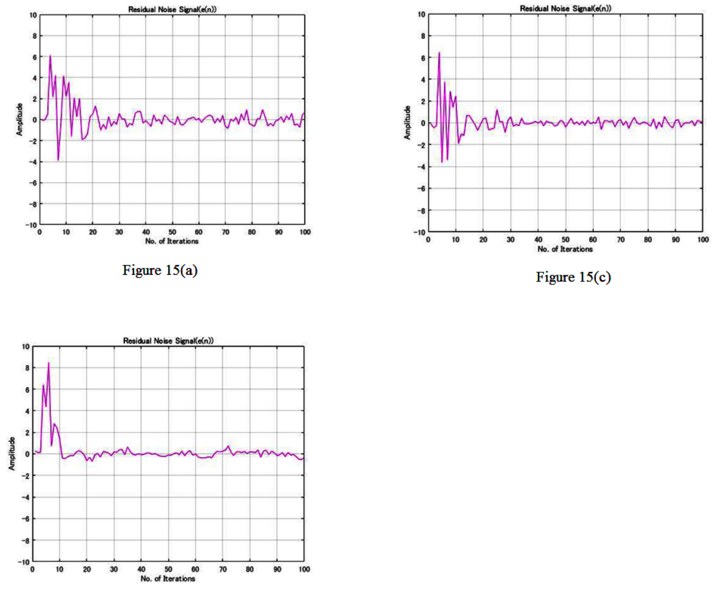


Figure 15(a) Figure 15(b) Figure 15(c)

Table 2 Comparison of the proposed APFxLMS with ANCs

	RNPL[dB]	NRS
Standard LMS	-12.4	44
APFxLMS	-20.2	17
Delay LMS	-15.3	18

From Table 2, it is clearly seen that APFxLMS demonstrate the best performance than other ANCs with/without secondary path modelling.

5 Conclusion

Comparing all the results, it is observed that the proposed method in this study presents a fast convergence speed than the delay LMS without secondary path modelling, which is generally preferred in ANC. The convergence speed of ANCs methods appears in the tap weight trajectory, which is the plots of the filter coefficients that show the stability of the proposed algorithm. In this regard, the proposed system takes a faster and relatively straight way to the optimal position than the delay LMS without secondary path modelling. Finally, the proposed algorithm obtains lower finite residual noise power (RNP) lower than -20dB, which demonstrate the best performance then other ANCs with/without secondary path modelling.

References

Wu, M, Chen, G, and Qiu, X, (2008), 'An improved active noise control algorithm without secondary path identification based on the frequency-domain sub band architecture', *IEEE Transactions on Audio, Speech, and Language Processing 16(8):1409-1419.*

Zhou, D, DeBrunner, V, (2007), 'A new active noise control algorithm that requires no secondary path identification based on the SPR property' *IEEE Transactions on Signal Processing 55(5):1719-1729.*

Caudana, EL, Betancourt, P, Cruz, E, Miyatake, MN, and Meana, HP, (2008), 'An Active Noise Cancelling Algorithm with Secondary Path Modelling', *In 12th WSEAS International Conference on Computers, Heraklion, Greece.*

Moazzam, Md, Rabbani, Md, S, (2013), 'Performance evaluation of different active noise control (ANC) algorithms for attenuating noise in a duct', *Master Thesis, Blekinge Institute of Technology, Sweden.*

Zhang, R, Xie Z, Zhang, X, (2010), 'An improved active noise control system without secondary path model', *In IEEE International Conference on Image Analysis and Signal Processing, pp. 454–459.*

Zhang, X, Ren, X, (2010), 'A novel active noise control using neural networks without the secondary path identification', *In 8th World Congress on Intelligent Control and Automation, China, July 2010.*

Kurczyk, S, Pawełczyk, M, (2014), 'Active noise control without secondary path modelling – Varying-Delay LMS approach', *In IEEE International Conference on Methods and Models in Automation and Robotics (MMAR).*

Kurczyk, S, Pawelczyk, M, (2014), 'Active noise control using a fuzzy inference system without secondary path modelling', *Archives of Acoustics **39**(2):243-248.*

Kajikawa, Y, Nomura, Y, (2000), 'Active noise control system without secondary path model', *Electronic Communications Japan 83(III): 47–55.*

Kajikawa, Y, Nomura, Y, (2003), 'Active noise control without a secondary path model by using a frequency-domain simultaneous perturbation method with variable perturbation', *I n IEEE International Conference on Acoustics, Speech, and Signal Processing, **V**: 580–583.*

Qiu, X, Gao, M, and Burnett, I, (2014), 'A comparison between adaptive ANC algorithms with and without cancellation path modelling', *In 21st International Congress on Sound and Vibration, Beijing, China, July 2014.*

Gao, M, Lu, J, and Qiu, X, (2016), 'A simplified sub-band ANC algorithm without secondary path modeling', *IEEE/ACM Transactions on Audio, Speech, and Language Processing* **24**(7): 1164- 1174.

Qatu, Mohamad S., (2012), 'Recent research on vehicle noise and vibration', *Int. J. of Vehicle Noise and Vibration 2012 - Vol. 8, No.4 pp. 289 – 30.*

Mondal (Das), K., Das, S., Abu, A. B. H., Hamada, N., Toh, H. T., Das, S., Faris, W. F., (2018), 'All-Pass Filtered-X least mean square Algorithm for Narrowband Active Noise Control', *Journal of Applied Acoustics, Vol. 142, pp. 1-10, Dec 2018.*

Qatu, Md. S., Abdelhamid, Md. K., Pang, J., Sheng, G., (2009), 'Overview of automotive noise and vibration', *Int. J. of Vehicle Noise and Vibration 2009 - Vol. 5, No.1/2 pp. 1 – 35*