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Novel Adaptive Fuzzy Feedback Neural Network Controller for Narrowband Active Noise Control System

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ABSTRACT With the development of science and technology in recent years, many operating machines have become sources of noise affecting quality of life. Hence, the topic of noise diminution using an active noise control (ANC) system has attracted many researchers. This paper develops a new adaptive fuzzy feedback neural network controller (AFFNNC) to improve the performance for narrowband active noise control (NANC) systems. The proposed controller combines fuzzy inference and adaptive feedback neural network controllers that are based on the filtered-s least mean square (FSLMS) algorithm. The AFFNNC comprises five network layers, in which the output layer of the controller uses an adaptive algorithm to tune directly the parameters of filters without prior training. The computational complexity, convergence and stability of the AFFNNC are analyzed. Evaluations are performed on both linear and nonlinear NANC systems with a recorded noise signal that was obtained from a transformer. Numerical simulations confirm the efficiency of the proposed controller compared with other ANC controllers.

INDEX TERMS Narrowband noise, active noise control, noise cancellation, adaptive fuzzy feedback neural controller.

I. INTRODUCTION

Noise has affected quality of our daily life, therefore, the way to reduce noise becomes a hot topic for researchers. Noise that is emitted by motors, fans, machines and automated equipment often has significant power at low frequency (below 500 Hz) [1]. However, conventional passive noise control (PNC) methods use soundproof materials, which are only effective at reducing high-frequency noise. In contrast, ANC method is effective at cancelling low-frequency noise [2]–[4]. Hence, ANC systems have attracted much attention in the last decade.

In terms of physical nature, the ANC method is based on the principle of superposition. A controller is used to generate a secondary sound wave, which has the opposite phase and the same amplitude as the primary sound wave. These two sound waves interfere with each other, canceling out the undesired noise. The performance of an ANC system depends on the properties of the primary and secondary paths, the delay time of the controller, and some other factors. In an ANC system, of which the primary and secondary paths transfer functions are assumed to be linear, a linear finite impulse response (FIR) filter based on the filtered-x least mean square (FXLMS) algorithm is commonly used because of its simplicity. Several ANC studies have been proposed to cancel undesired noise with linear primary and secondary paths [5]–[8]. However, the FIR filter with the FXLMS algorithm performs poorly when the ANC is nonlinear [9], [10]. In order to solve this problem, many algorithms of nonlinear controllers were proposed. A genetic algorithm-based ANC system has been proposed [10], and adaptive Volterra controllers have been developed for handling nonlinear ANC systems [11]–[13]. Adaptive neural network controllers have also been introduced [14]–[16]. Functional link artificial neural network (FLANN) structures were developed to cancel noise by exploiting FSLMS algorithms [17]–[21]. Notably, the FSLMS algorithm is widely used in FLANN structures due to its ability to update the controller coefficients online and to improve noise reduction performance [22]. Haseeb *et al.* proposed calculating the instantaneous gain of

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auxiliary noise based on fuzzy logic for online feedback path modeling and neutralization in ANC systems [23]. Le *et al.* developed an adaptive filter for ANC systems using a recurrent type-2 fuzzy brain emotional learning neural network [24]. Peng *et al.* used the Takagi–Sugeon–Kang (TSK) type fuzzy logic-based feedforward ANC system [25]. Zhang introduced the recurrent fuzzy neural network controller for ANC [26]. Devi *et al.* mentioned an environmental noise reduction system that uses adaptive fuzzy and fuzzy neural network algorithms [27]. Markedly, the combination of neural network and fuzzy logic is appropriate for controlling and modeling nonlinear systems. A neural network controller can learn accurately from the training data, but it eclipses with inferential properties. In contrast, a fuzzy logic controller can perform its logical reasoning but it lacks self-regulation and the capacity of learning to adapt to nonlinear systems. Thus, fuzzy and neural-network controllers can be combined to solve these problems for cancelling noise, saving time to search for the optimal solution. However, most studies of adaptive fuzzy neural controllers are based on conventional adaptive neural filters [28]–[30], and their performance only reaches certain limits.

From the above analysis, the adaptive fuzzy neural network controller can be used for noise cancellation. The FSLMS algorithm can directly update the adaptive parameters, and significantly improve the noise cancellation performance. Thus, this work proposes an adaptive fuzzy feedback neural network controller (AFFNNC) that is based on the FSLMS algorithm, which integrates the expert property of the fuzzy inference controller and learning capacity of the neural network to adapt nonlinear ANC systems. The structure of the presented AFFNNC consists of five network layers, of which the output layer has a feedback component that returns to its input for monitoring, recognizing, and emitting time-varying patterns and self-adjusting adaptive parameters to perform noise cancellation [16]. Furthermore, an adjustment parameter of the feedback component helps the ANC system to reach equilibrium [16].

Contributions of this work consist of the following.

(1) Design an AFFNNC in which the fuzzy network layers have expert knowledge-based fuzzy inference properties, and the feedback adaptive neural network layers execute fast learning algorithm without prior training.

(2) Analyze the proposed algorithm, including the convergence and stability of the controller.

(3) Confirm the effectiveness of the presented controller by analyzing the computational complexity and performing simulations through comparison with other ANC controllers.

The rest of this paper is shown as follows. Section II expresses the proposed work and considers its convergence and stability conditions. Section III analyzes the computational complexity of the proposed controller with existing ANC controllers. Section IV compares the performance of the proposed work with other ANC controllers by simulation results. Section V draws conclusions.

II. PROPOSED CONTROLLER AND ANALYSIS

This section introduces the algorithm of the proposed controller, and analyzes its the convergence and stability.

A. PROPOSED ALGORITHM

The proposed controller is built in a parallel structure, shown in Fig. 1. In which, $S(z)$ and $P(z)$ are the transfer functions of the secondary and primary paths, respectively. $d(m)$ is the primary noise signal which consists of k harmonic components at frequency ω_i $(i = 1, 2, \ldots, k)$,

$$d(m) \equiv \sum_{i=1}^{k} \cos(\omega_i m) + u(m), \tag{1}$$

where $u(m)$ denotes the disturbance, and m is the number of the digital time sample. The i^{th} reference sinusoidal signal is emitted by the signal generator, when it receives the synchronous signal from a non-acoustic sensor,

$$x_i(m) = \cos(\omega_i m). \tag{2}$$

The error signal is defined as

$$e(m) = d(m) - y_s(m), \tag{3}$$

where $y_s(m) = s(m) * y(m)$, $s(m)$ is the impulse response of $S(z)$. Suppose that $e(m) = e_1(m) + e_2(m) + \ldots + e_k(m)$ is the sum of the error signals from each channel and the $e_i(m)$ is the error signal at the i^{th} channel, which is obtained by filtering the error signal $e(m)$ using the bandpass filter $B_i(z)$ with transfer function [31]

$$B_i(z) = \left(\frac{1 - a_i^2}{1 + a_i^2}\right)\left(\frac{b_i z^{-1} - (1 + a_i^2)z^{-2}}{1 - b_i z^{-1} + a_i^2 z^{-2}}\right), \tag{4}$$

where $b_i = (1 + a_i^2)cos\omega_i$ is the parameter that controls the central frequency of the passband at the i^{th} channel, and a_i is area that establishes the bandwidth of the bandpass filter with $0 < a_i < 1$ and $|b_i| < 2a_i$.

Fig. 2 expresses the structure of the AFFNNC, which includes five network layers. Here, for simplicity, only a single input and a single output of fuzzy linguistic variables are analyzed for the i^{th} channel. The algorithm of the AFFNNC is described as follows.

Layer 1 (Input Layer): The nodes of network layer 1 receive input signal at the i^{th} channel, and transmit it directly to layer 2. The output signal of layer 1 ($\Upsilon_i^{(1)}(m)$) is

$$\Upsilon_i^{(1)}(m) = x_i(m). \tag{5}$$

Layer 2 (M Nodes): The "M" nodes replace membership functions to display the input and output fuzzy linguistic variables. Fuzzy sets are established for each input and output fuzzy linguistic variables. The Gaussian membership functions are chosen as

$$\Upsilon_{j,i}^{(2)}(m) = \exp\left\{-\frac{\left(\Upsilon_i^{(1)}(m) - c_{j,i}\right)^2}{\varpi_{j,i}^2}\right\}, \tag{6}$$

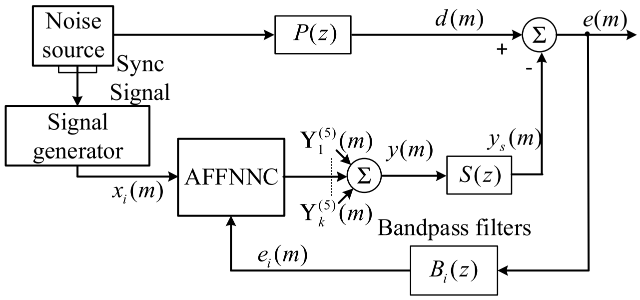

FIGURE 1. Block diagram of proposed AFFNNC.

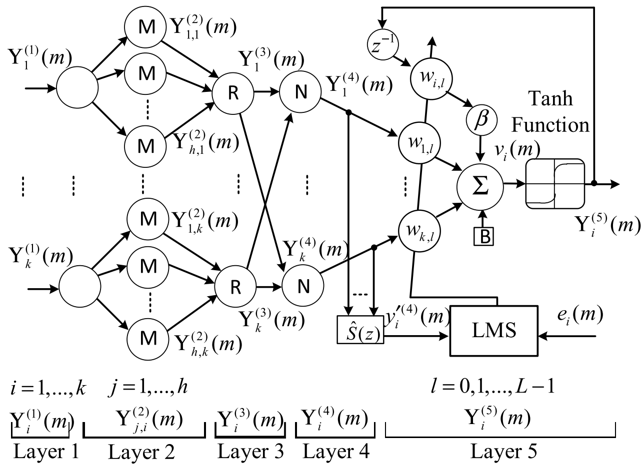

FIGURE 2. Structure of the AFFNNC.

where the adjustable parameters $\varpi_{j,i}$ and $c_{j,i}$ are the width and center of the Gaussian membership functions of the j^{th} fuzzy set of input and output of fuzzy linguistic variables, respectively, with $j = 1, 2, \ldots, h$ at the i^{th} channel. These parameters can be determined based on experience. The output signal of layer 2 ($Y_{j,i}^{(2)}(m)$) depends on each corresponding fuzzy set.

Layer 3 (Reasoning Layer): The "R" nodes represent fuzzy rules, which perform "If-then" rules, inferred by expert knowledge to compute the firing strength,

$$Y_i^{(3)}(m) = \prod_{j=1}^{h} Y_{j,i}^{(2)}(m). \tag{7}$$

The output signal of the layer 3 ($Y_i^{(3)}(m)$) depends on each fuzzy law. h fuzzy rules correspond to the input and output fuzzy linguistic variables at the i^{th} channel.

Layer 4 (N Nodes): The "N" nodes carry out the normalization of the firing strengths from layer 3 to prepare for defuzzification. The output signal of layer 4 is

$$Y_i^{(4)}(m) = \frac{Y_i^{(3)}(m)}{\sum_{i=1}^{k} Y_i^{(3)}(m)}. \tag{8}$$

Layer 5 (Output Layer): This layer is the adaptive feedback neural network layer which performs adaptive defuzzification. The weights of this layer represent the singleton constituents [28]. The output signal of the output layer is gone through the Tanh activation function and defined by

$$Y_i^{(5)}(m) = \mathrm{Tanh}(v_i(m)) = \frac{\exp(v_i(m)) - \exp(-v_i(m))}{\exp(v_i(m)) + \exp(-v_i(m))}, \tag{9}$$

with

$$v_i(m) = \sum_{l=0}^{L-1} \Big(w_{i,l}(m) Y_i^{(4)}(m-l) + \beta w_{i,l}(m) Y_i^{(5)}(m-l-1) + B \Big), \tag{10}$$

where β is the adjustment parameter for the feedback component and B is the bias parameter. The cost function at the i^{th} channel is determined as $\xi_i(m) = e_i^2(m)$. The weights of layer 5 at the i^{th} channel will be adapted according to the gradient descent based adaptive law as

$$\boldsymbol{w}_i(m+1) = \boldsymbol{w}_i(m) - \frac{\mu_i}{2} \nabla \boldsymbol{\xi}_i(m), \tag{11}$$

$\boldsymbol{w}_i(m) = \left[w_{i,0}(m), w_{i,1}(m), \ldots, w_{i,L-1}(m)\right]^T$ and the instantaneous gradient estimation vector of layer 5 is

$$\nabla \boldsymbol{\xi}_i(m) = 2e_i(m) \left[\nabla \boldsymbol{e}_i(m)\right], \tag{12}$$

where $\nabla \boldsymbol{e}_i(m)$ is the error gradient vector at the i^{th} channel. Applying the chain rule to $\nabla \boldsymbol{e}_i(m)$ yields,

$$\begin{aligned} \nabla \boldsymbol{e}_i(m) &= \frac{\partial e(m)}{\partial y_s(m)} \frac{\partial y_s(m)}{\partial y(m)} \frac{\partial y(m)}{\partial Y_i^{(5)}(m)} \\ &\quad \times \frac{\partial Y_i^{(5)}(m)}{\partial v_i(m)} \left[\frac{\partial v_i(m)}{\partial w_{i,0}(m)}, \cdots, \frac{\partial v_i(m)}{\partial w_{i,L-1}(m)} \right]^T \\ &= -s(m) \left(1 - \left[Y_i^{(5)}(m) \right]^2 \right) \\ &\quad \times \left[\frac{\partial v_i(m)}{\partial w_{i,0}(m)}, \cdots, \frac{\partial v_i(m)}{\partial w_{i,L-1}(m)} \right]^T, \end{aligned} \tag{13}$$

where $\frac{\partial e(m)}{\partial y_s(m)} = -1$, $\frac{\partial y_s(m)}{\partial y(m)} = s(m)$, $\frac{\partial y(m)}{\partial Y_i^{(5)}(m)} = 1$,

$$\begin{aligned} \frac{\partial Y_i^{(5)}(m)}{\partial v_i(m)} &= \frac{\partial}{\partial v_i(m)} \left(\frac{\exp(v_i(m)) - \exp(-v_i(m))}{\exp(v_i(m)) + \exp(-v_i(m))} \right) \\ &= 1 - \left[Y_i^{(5)}(m) \right]^2. \end{aligned}$$

Suppose

$$\begin{aligned} v'_{i,l}(m) &\equiv \frac{\partial v_i(m)}{\partial w_{i,l}(m)} \\ &= Y_i^{(4)}(m-l), \quad l = 0, 1, \ldots, L-1, \end{aligned} \tag{14}$$

and substitute (14) into (13), we have

$$\nabla \boldsymbol{e}_i(m) = -s(m) \left(1 - \left[Y_i^{(5)}(m) \right]^2 \right) \left[v'_{i,0}(m), \cdots, v'_{i,l}(m) \right]^T. \tag{15}$$

Therefore, (15) can be modified using the FSLMS algorithm [22]

$$\begin{aligned} \nabla \boldsymbol{e}_i(m) &= -\left(1 - \left[Y_i^{(5)}(m) \right]^2 \right) \hat{s}(m) \\ &\quad \times \left[Y_i^{(4)}(m), \ldots, Y_i^{(4)}(m-q) \right]^T \end{aligned}$$

$$= -\left(1-\left[\mathrm{Y}_i^{(5)}(m)\right]^2\right)\boldsymbol{y'}_i^{(4)}(m), \tag{16}$$

where $\hat{s}(m)$ is the impulse response of the filter $\hat{S}(z)$, $\boldsymbol{y}_i^{\prime(4)}(m) = \left[y_i^{\prime(4)}(m), \ldots, y_i^{\prime(4)}(m-L+1)\right]^T$ is the filtered signal vector of layer 4, and the filtered signals are

$$y_i^{\prime(4)}(m) = \sum_{q=0}^{Q-1} \hat{s}_q(m)\mathrm{Y}_i^{(4)}(m-q), \tag{17}$$

where $\hat{s}_q(m)$ is the q^{th} coefficient of the filter $\hat{S}(z)$.

Substituting (12) and (16) into (11), the weights of layer 5 at the i^{th} channel are updated by

$$\boldsymbol{w}_i(m+1) = \boldsymbol{w}_i(m) + \mu_i\left(1-\left[\mathrm{Y}_i^{(5)}(m)\right]^2\right)e_i(m)\boldsymbol{y'}_i^{(4)}(m), \tag{18}$$

where the μ_i is the learning rate at the i^{th} channel of the AFFNNC.

B. CONVERGENCE AND STABILITY OF THE PROPOSED CONTROLLER

The convergence and stability of proposed controller are assured when all the channels of the proposed work are converged and stabilized. Therefore, the boundary condition of the learning rate μ_i of the proposed controller must be considered to achieve convergence and stability at the i^{th} channel. Taylor expansion of the error functions yields

$$e_i(m+1) = e_i(m) + \nabla\boldsymbol{e}_i(m)\Delta\boldsymbol{w}_i(m) + \text{h.o.t.}, \tag{19}$$

where "h.o.t." stands for higher-order terms, and $\Delta\boldsymbol{w}_i(m)$ is given by

$$\begin{aligned}\Delta\boldsymbol{w}_i(m) &= \boldsymbol{w}_i(m+1) - \boldsymbol{w}_i(m)\\ &= \mu_i\left(1-\left[\mathrm{Y}_i^{(5)}(m)\right]^2\right)e_i(m)\boldsymbol{y'}_i^{(4)}(m).\end{aligned} \tag{20}$$

From (16) and (20), (19) can be rewritten as

$$\begin{aligned}e_i(m+1) &= e_i(m) + \nabla\boldsymbol{e}_i(m)\Delta\boldsymbol{w}_i(m) + \text{h.o.t.}\\ &= e_i(m) - \left(1-\left[\mathrm{Y}_i^{(5)}(m)\right]^2\right)\boldsymbol{y'}_i^{(4)}(m)\\ &\quad\times\mu_i\left(1-\left[\mathrm{Y}_i^{(5)}(m)\right]^2\right)e_i(m)\boldsymbol{y'}_i^{(4)}(m) + \text{h.o.t.}\\ &= e_i(m)\left[1-\mu_i\left(1-\left[\mathrm{Y}_i^{(5)}(m)\right]^2\right)^2\left\|\boldsymbol{y'}_i^{(4)}(m)\right\|^2\right]\\ &\quad+\text{h.o.t.},\end{aligned} \tag{21}$$

where $\|\bullet\|$ is the Euclidean norm.

In order to guarantee convergence, the i^{th} error signal at the next time step $(m+1)$ must be less than or equal to the i^{th} error signal at the current time step m. Accordingly, (21) must satisfy the following condition

$$\begin{aligned}|e_i(m+1)| \le &\left|e_i(m)\left[1-\mu_i\left(1-\left|\mathrm{Y}_i^{(5)}(m)\right|^2\right)^2\left\|\boldsymbol{y}_i^{\prime(4)}(m)\right\|^2\right]\right|\\ &+|\text{h.o.t.}|\,.\end{aligned} \tag{22}$$

With a sufficient small step size, the "h.o.t." can be constrained to zero [32]; therefore, the learning rate μ_i is determined as

$$0 < \mu_i < \frac{1}{\left(1-\left|\mathrm{Y}_i^{(5)}(m)\right|^2\right)^2\left\|\boldsymbol{y}_i^{\prime(4)}(m)\right\|^2}. \tag{23}$$

Since $-1 < \mathrm{Y}_i^{(5)}(m) < 1$ (according to (9)), we have

$$\begin{aligned}\left(1-\left|\mathrm{Y}_i^{(5)}(m)\right|^2\right)^2\left\|\boldsymbol{y}_i^{\prime(4)}(m)\right\|^2 &< \left\|\boldsymbol{y}_i^{\prime(4)}(m)\right\|^2\\ &\le \max\left\|\boldsymbol{y}_i^{\prime(4)}(m)\right\|^2.\end{aligned} \tag{24}$$

If the learning rate μ_i is selected to satisfy

$$0 < \mu_i < \frac{1}{\max\left\|\boldsymbol{y'}_i^{(4)}(m)\right\|^2}, \tag{25}$$

then the ANC system at the i^{th} channel is locally convergent and stable.

III. COMPUTATIONAL COMPLEXITY

This section compares the computational cost of the proposed controller with other nonlinear ANCs including Huynh's work [16] relating to adaptive feedback neural network controller based on FXLMS algorithm, Zhang's work [28] involving adaptive fuzzy neural network and Das's work [22] concerning FLANN based on the FSLMS algorithm. Most of the calculations depend on the lengths of the estimated secondary path Q and the adaptive filter L. Table 1 provides the details.

For the proposed controller, the filtered error signal for each channel is calculated by (4), which implements five multiplications and four additions. The output of layer 5 is calculated using (9), requiring four exponentiations, two additions, and one division for each channel. Calculating the output of each channel of layer 5 using (10) requires $L+2$ multiplications and $L+1$ additions. The computation of the filtered signal in (17) involves Q multiplications and $Q-1$ additions. Finally, updating of the weights in (18) carries out $L+1$ additions and $L+3$ multiplications for each channel. Hence, $k(2L+Q+10)$ multiplications, $k(2L+Q+7)$ additions, $4k$ exponentiations, and k divisions for k channels are performed. Besides, Huynh [16] built the ANC in a parallel structure for each narrowband channel. Two adaptive filters were used in the controller. The computational complexity for k channels is $k(2L+2Q+9)$ multiplications, $k(2L+2Q+2)$ additions, k divisions, and k exponentiations. The computational cost of Zhang's work [28] includes $Q+L+2$ multiplications and $Q+L-1$ additions for each channel; therefore, the total computational cost includes $k(Q+L+2)$ multiplications and $k(Q+L-1)$ additions for k channels. At last, the computational cost of Das's work [22] includes $k(L(2P+1)(Q+3)-Q)$ multiplications and $k(L(2P+1)(Q+1)+1)$ additions, where P is the order of trigonometric functional expansion.

Choosing $L = Q = 100$, $P = 1$ and $k = 3$, the specific computational costs of the controllers are shown in the Table 2. Though the computational cost of the proposed controller is higher than that of the work in [28], but is smaller than the other cases. The trade-off between performance and computational cost of the proposed work can thus be considered. The performance of the proposed controller will be considered in the section IV.

IV. SIMULATION RESULTS

In this section, the controller performance is compared with several other ANC controllers to demonstrate the effectiveness of the proposed controller. Only a single input and a single output of fuzzy linguistic variables are used at the layer 2. The parameters of six fuzzy sets ($h = 6$) using the Gaussian membership function are chosen as follows.

Parameters of the input fuzzy linguistic variable:

$$c_{j,i} = \{-1, -0.6, -0.2, 0.2, 0.6, 1\}, \tag{26}$$

$$\varpi_{j,i} = \{0.35, 0.2, 0.2, 0.2, 0.2, 0.35\}. \tag{27}$$

Parameters of the output fuzzy linguistic variable:

$$c_{j,i} = \{-1, -0.6, -0.2, 0.2, 0.6, 1\}, \tag{28}$$

$$\varpi_{j,i} = \{0.17, 0.17, 0.17, 0.17, 0.17, 0.17\}. \tag{29}$$

These parameters of the Gaussian membership function are selected based on experience and trial-and-error method. Figure 3 illustrates the six fuzzy sets of input and output variables, where A1-A6 and B1-B6 are Gaussian membership functions of the input and the output variables. Table 3 displays six fuzzy rules corresponding to each fuzzy set of input and output variables.

For the conventional narrowband active noise control (NANC) method uses only FIR filters [2], and μ_i is the step size at i^{th} channel for the simulation setting. For Huynh [16], two learning rate parameters (μ_{1i} and μ_{2i}) are used at i^{th} channel due to the use of two adaptive filters, B is the bias parameter and α is the adjustment parameter for the feedback component. For Zhang [28] approach, the learning rate parameter μ_i is set at i^{th} channel for updating the weights of the output layer of the controllers. For Das [22], P is the order of trigonometric functional expansion, and the learning rate parameter at i^{th} channel is μ_i to tune the weights of the FIR filters. The setting values are shown in the Table 4.

A. CASE 1

In this case, the ANC system is linear. The transfer functions of the primary and secondary paths are selected as [6], [33].

$$P(z) = z^{-5} - 0.3z^{-6} + 0.2z^{-7}, \tag{30}$$

$$S(z) = z^{-2} + 1.5z^{-3} - z^{-4}, \tag{31}$$

where the primary noise consists of three frequencies with amplitude 0.6 (200Hz, 400Hz and 600Hz) and a zero-mean white noise signal with amplitude 0.1. Parameters of the bandpass filters at three channels are $a_1 = 0.9$, $b_1 = 1.7877$, $a_2 = 0.9$, $b_2 = 1.7214$, $a_3 = 0.9$, and $b_3 = 1.6127$.

TABLE 1. Comparisons of computational cost.

Controllers	$\times$	$+,-$	$\div$	$e^{(\cdot)}$
Huynh [16]	$k(2L+2Q+9)$	$k(2L+2Q+2)$	k	k
Zhang [28]	$k(Q+L+2)$	$k(T+Q-1)$		
Das [22]	$k(L(2P+1) \times (Q+3)-Q)$	$k(L(2P+1) \times (Q+1)+1)$		
Proposed controller	$k(2L+Q+10)$	$k(2L+Q+7)$	k	$4k$

TABLE 2. Total computational cost of controllers.

Controllers	$L=Q=100$, $P=1$, $k=3$.			
	$\times$	$+,-$	$\div$	$e^{(\cdot)}$
Huynh [16]	1227	1206	3	3
Zhang [28]	606	597		
Das [22]	92400	90903		
Proposed controller	930	921	3	12

Using (25), the learning rate is calculated as $0 < \mu_i < 1/_{\max} \left\| \boldsymbol{y'}_i^{(4)}(n) \right\|^2 = 0.00073$. Therefore, the learning rate of the proposed controller is chosen as $\mu_i = 8 \times 10^{-5}$ to satisfy the convergence and stability conditions. The performance of a controller is determined by a learning curve based on the mean square error (MSE). The MSE is computed by $1/e^2$ with a reduction $10\log_{10}(1/e^2)$. Fig. 4 plots the learning curve of the MSE for the other ANC controllers. The results indicate that the noise cancellation is effective at all frequencies for the linear ANC systems. In which, NANC [2] has slow convergence despite having the same step size as proposed controller. This proves that satisfying the learning rate parameters in (25) helps the proposed controller to easily achieve fast convergence and stability.

B. CASE 2

The ANC system in case 2 is implemented with nonlinear secondary and primary paths. The secondary acoustic path is set as a Volterra series [16]

$$y_s(m) = y(m) + 0.35y(m-1) + 0.09y(m-2) - 0.5y(m)y(m-1) + 0.4y(m)y(m-2). \tag{32}$$

The primary acoustic path is defined as

$$d(m) = g(m-2) + 0.08\,[g(m-2)]^2 - 0.04\,[g(m-2)]^3, \tag{33}$$

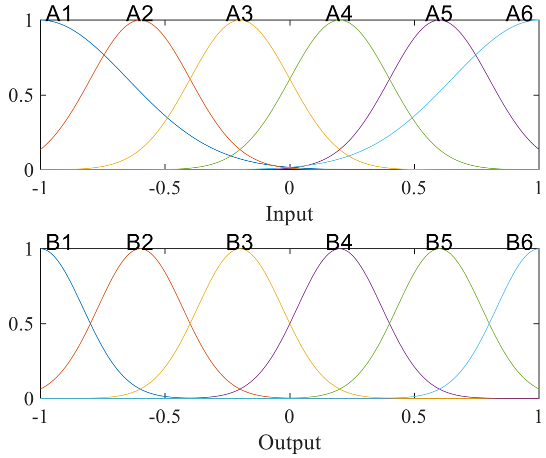

FIGURE 3. Six fuzzy sets of input and output variables, where A1-A6 and B1-B6 are Gaussian membership functions of input and output variables.

TABLE 3. Fuzzy rules.

Numbers	Rules
1.	If Input is A1 then Output is B1
2.	If Input is A2 then Output is B2
3.	If Input is A3 then Output is B3
4.	If Input is A4 then Output is B4
5.	If Input is A5 then Output is B5
6.	If Input is A6 then Output is B6

where $g(m)$ is given by

$$g(m) = 0.8x(m-2) - 0.9x(m-3) + 0.9x(m-4), \quad (34)$$

with $x(m)$ contains three frequencies with amplitude 0.6 ($300Hz$, $450Hz$ and $600Hz$) and a zero-mean white noise signal with amplitude 0.1. Parameters of the bandpass filters are set to correspond with three new channels: $a_1 = 0.9$, $b_1 = 1.7600$, $a_2 = 0.9$, $b_2 = 1.6981$, and $a_3 = 0.9$, $b_3 = 1.6127$. Fig. 5 shows the performance. The methods from Das, Zhang and Huynh present similar performance to restrain the narrowband noise. But the results demonstrate that the proposed controller performs better than the other ANC controllers for the nonlinear system.

C. CASE 3

The noisy signal is replaced by an actual narrowband noise signal recorded from a transformer. In this experiment, the narrowband noise signals at frequencies below $1kHz$ are eliminated. Fig. 6 shows the narrowband noise frequencies, including nine narrowband noise with frequencies: $241Hz$, $361Hz$, $481Hz$, $507Hz$, $601Hz$, $721Hz$, $841Hz$, $961Hz$ and $994Hz$.

All parameters are the same as in the case 2, but the learning rate is 0.0003 to test the effectiveness in canceling the recorded transformer noise. The parameters of the bandpass filters are $a_1 = 0.9$, $b_1 = 1.7777$, $a_2 = 0.9$, $b_2 = 1.7377$, $a_3 = 0.9$, $b_3 = 1.6824$, $a_4 = 0.9$, $b_4 = 1.6684$, $a_5 = 0.9$, $b_5 = 1.6121$, $a_6 = 0.9$, $b_6 = 1.5275$, $a_7 = 0.9$, $b_7 = 1.4293$, $a_8 = 0.9$, $b_8 = 1.3185$, $a_9 = 0.9$, and $b_9 = 1.2859$. Fig 7 displays the learning curve. The proposed controller still has the highest performance.

TABLE 4. Setting parameters for controllers.

Controllers	Case 1	Case 2	Case 3
NANC [2]	$\mu_i = 8\times10^{-5}$		
Huynh [16]		$\mu_{1i} = 0.7$ $\mu_{2i} = 6\times10^{-3}$ $\alpha = 10^{-3}$ $B = 4\times10^{-5}$	$\mu_{1i} = 0.9$ $\mu_{2i} = 8\times10^{-4}$ $\alpha = 10^{-3}$ $B = 4\times10^{-5}$
Zhang [28]		$\mu_i = 5$	$\mu_i = 10$
Das [22]		$P=1$ $\mu_i = 6\times10^{-5}$	$P=1$ $\mu_i = 6\times10^{-5}$
Proposed controller	$\mu_i = 8\times10^{-5}$ $\beta = 10^{-3}$ $B = 4\times10^{-5}$	$\mu_i = 10^{-4}$ $\beta = 10^{-3}$ $B = 4\times10^{-5}$	$\mu_i = 3\times10^{-4}$ $\beta = 10^{-3}$ $B = 4\times10^{-5}$

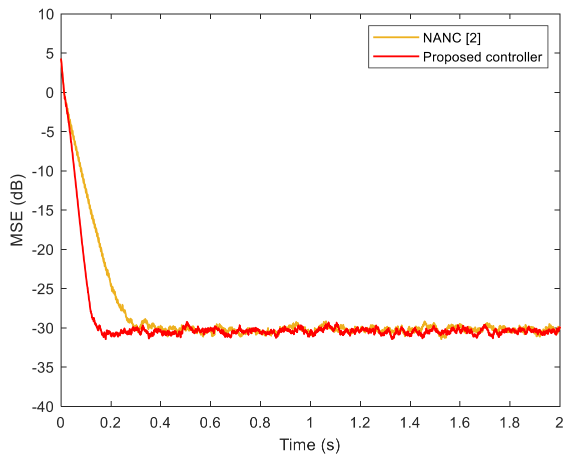

FIGURE 4. Learning curve for ANC controllers.

Based on the above three experimental cases, the proposed controller has shown outstanding performance compared to the other ANC methods that have been investigated on nonlinear and linear ANC systems, with noise signal recorded from a transformer and tonal noises. Therefore, it can be concluded that the effectiveness of the proposed controller is a combination of the following five factors. The first factor involves the parallel structure combined with bandpass filters, it has been verified for improving performance in narrowband ANC systems [8], [31]. The second factor is the efficient combination of the feedback neural network layers and the fuzzy inference layers based on trial-and-error method to achieve good performance. The third factor has a feedback

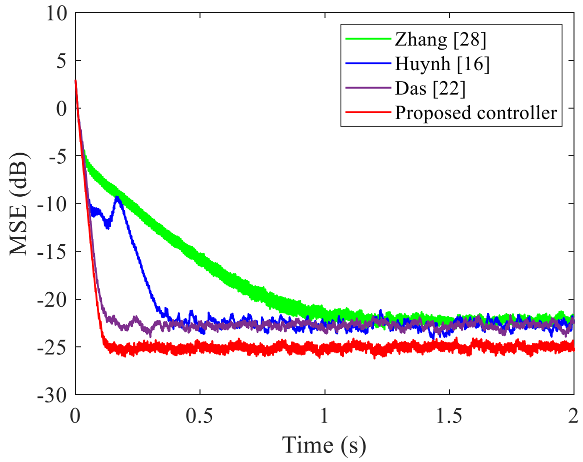

FIGURE 5. Noise reduction performance of ANC controllers.

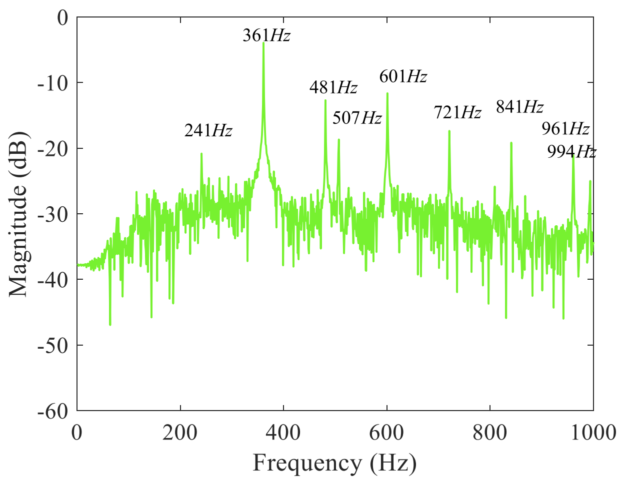

FIGURE 6. Primary noise signal of transformer in frequency range below 1kHz.

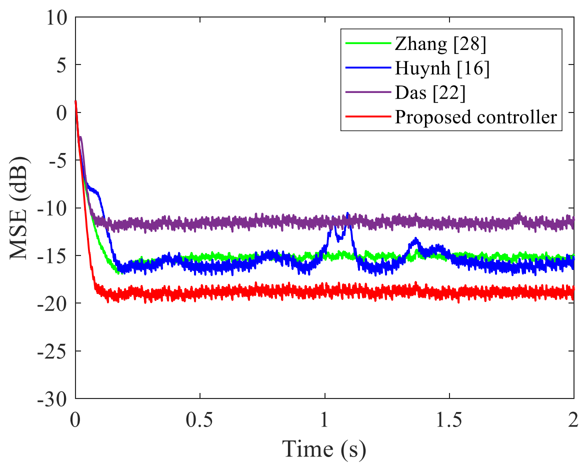

FIGURE 7. Error signals of ANC controllers.

component from the output of layer 5 that returns to its input, it is capable of monitoring, recognizing, and emitting time-varying patterns to perform self-adjusting adaptive parameters for the ANC system [16]. The next factor uses bias parameter B and the adjustment parameter β, which have been chosen experimentally on the basis of trial-and-error method to reach steady equilibrium in experiments. This has been effectively confirmed by [16]. The last factor achieves the fast convergence and stabilization of the proposed method due to satisfying the boundary condition in (25).

V. CONCLUSION

This paper performed the algorithm analysis of the AFFNNC as well as the conditions to ensure the convergence and stability of the proposed controller. The computational complexity of the AFFNNC has also been compared with other ANC controllers. The results of simulations proved the superior performance of the AFFNNC in three experimental cases. Moreover, the fast convergence and stability were the advantages of the AFFNNC. Despite its high computational cost, the proposed work achieved better control performance in each experiment. Hence, proposed controller based on the FSLMS algorithm can be regarded effective at canceling noise in linear and nonlinear NANC systems.

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