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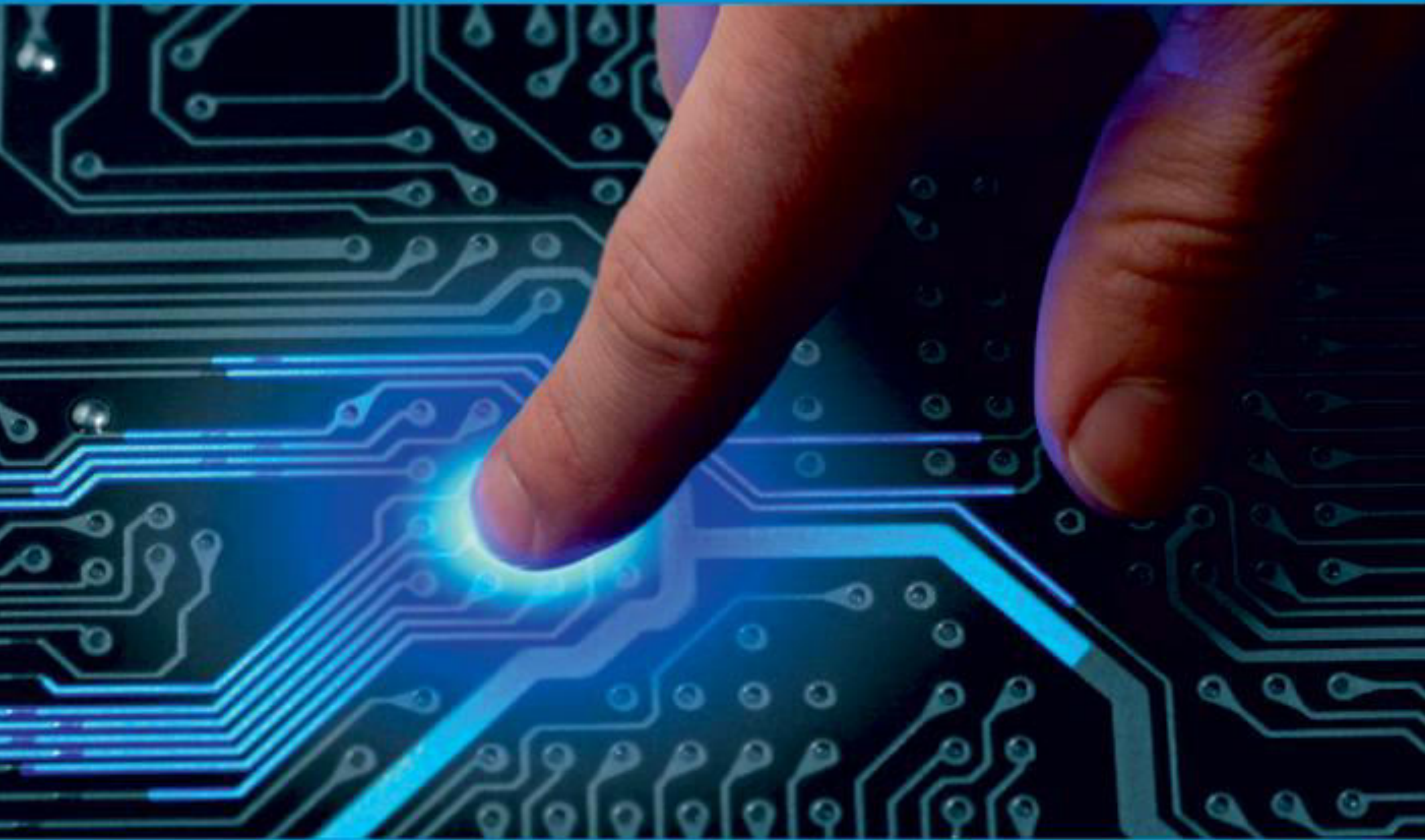

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# Comparison between the Non-Recurrent and Recurrent Neural Networks for Noise Cancellation

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**ABSTRACT:** The Artificial neural networks are one of the important development s that aim toremove noise from voice recognition devices .in this paper we use the feed forward neural networks with a dual extended adaptive filtering algorithm to remove nonstationary and colored noise from voice signal. Two techniques has been used in this paper, in order to make an effective noise cancelation, these are Recurrent Neural Network and Non-Recurrent Neural Network. Simulation of these two techniques has been carried out using MATLAB/Simulink packages and comparison has been conducted between the two techniques which revealed that Non-Recurrent Neural Network technique processes the data faster than the Recurrent Neural Network technique in terms of time . But the Recurrent Neural Network technique is more accurate than the Non-Recurrent Neural Network technique when the Root main square (RMS)algorithm is used .

**KEYWORDS**: *adaptive filte*r, linear filter,dynamic neural network, NARX

## I. INTRODUCTION

In noisy acoustic environment, audio signal in speech communication from mobile phone, moving car, train, aero plane, or over a noisy telephone channel is corrupted by additive random noise. The noise is unwanted signal and it is desirable to remove noise from original signal. Since noise is random process and varying at every instant of time, it should be estimated frequently to perform the noise cancellation. There are many schemes for noise removal but most effective scheme to accomplish noise cancellation is to use adaptive filters.

Effects of audio noise are experienced in our daily lives when using mobile phone in moving car, train, aero-plane, or talking over anoisy telephone channel. This noise contaminates the original information bearing signal with noise from its surrounding environment.

This noise should be removed to have effective communication between two ends [1].

Noise is a random process so it should be estimated at every instant in order to purify the desired signal from a noisy signal. Noise cancellation in variable, noisy and non-stationary environments is usually accomplished by means of adaptive filters. In adaptive filters [2], [3], [4], two inputs are required:

- Noise
- Primary signal + Noise

There are many adaptive filters and their applications are available in literature [4], [5], [6] but most commonly used adaptive filter is Windrow’s and Hoff's that applying Least Mean Square (LMS).

LMS is used because of its robustness, good tracking capabilities and simplicity both in terms of computational load and easiness of implementation. It is implemented using Finite Impulse Response (FIR) filter and first order weight updating equation. It has therefore been successfully applied to wide variety of applications [4].

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## II. DESIGN OF ADAPTIVE NOISE CANCELLER

Inorder to build the system in this paper and achieve an Adaptive Noise Canceller (ANC)the following example are considered.

In airplane pilot's voice is corrupted with the noise from the airplane's engines. Let us consider that desired signal is the pilot's voice which is represented by $x(n)$.

A microphone is placed near the engine that will pick up the engine noise from it. Let uscall that noise is $v(n)$. Another microphone near pilot will pick up both pilot voice and noise from engine.

Our objective is to develop a system that remove the engine noise from pilot's voice and give only output which contain the filtered signal.

Adaptive filter works on principle of minimizing mean square error between the desired output and filter output. Weights of the adaptive filter adapt in such a way that error is minimized and desired output is obtained. Error minimization criteria is different for different adaptive filters and hence their performance will be in different situations.

An adaptive filter can be a combination of

- Single-input or multi-input filters
- Linear or nonlinear filters
- FIR or IIR filters

In thispaper, both (FIR) and (IIR) filters are implemented for (ANC). Linear (FIR) filters are most commonly used because of their stability and relative ease of adaptation.

It is not possible to remove the engine noise from the pilot's microphone directly, since the engine noise was received in the pilot's microphone, and the engine noise received in the reference microphone are not the same signal. These two signals are uncorrelated with each other. There are differences in amplitude and time delay. Also, these differences are not fixed. They change with time and pilot's microphone position with respect to the airplane engine, and many other factors. Above all, noise is a random process and is varying at every instant of time. At every instant the noise is estimated and removed from the pilot's audio signal.

Therefore, designing the fixed filter to perform the task would not obtain the desired results. The application requires adaptive filter.

Adaptive filter processes the engine noise and make it equal to noise contaminating the speech signal. Then noise is subtracted from noisy signal to get noise free speech signal. In cases such as receiver of a telecommunication system, where there is no access to instantaneous value of contaminating noise and only noisy signal is available, complete noise cancellation isn't possible. However, noise reduction can be achieved in an average sense, using the statistics of the signal and the noiseprocess in such cases [1]. The noise cancellation system is used as shown in figure (1):

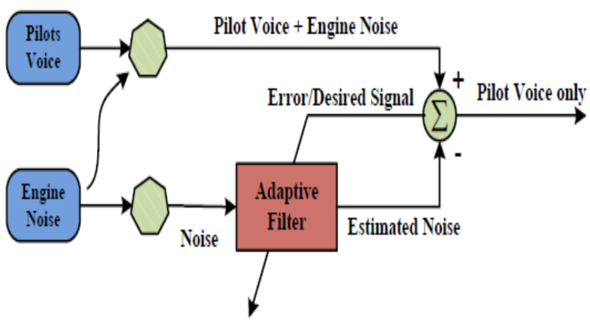


Fig.1. Noise cancellation system

The (LMS) adaptive filteringwas selected for removing the effects of engine noise on pilot's voice.

Figure (1) illustrates the basic principles of adaptive noise canceling. The input to the adaptive filter is engine noise signal $v(n)$and is uncorrelated with the pilots voice signal $x(n)$.The reference signal $v(n)$is filtered through adaptive filter to produce the output that is an estimate of the noise $v(n)$.

This output is then subtracted from the noisy signal $(x(n)+v(n))$to produce the system output $y(n)$. This is also called error signal. Error is feedback to adaptive algorithm block. Actually, error signal is the "desired signal" for noise

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canceller which eventually becomes the output for noise canceller. Mathematically desired signal is given by equation (1).

$$DS = [x(n) + v(n)] - y(n)(1)$$

Where ***DS*** is desired signal ,***y(n)*** is output of adaptive filter i.e. estimate of noise at input of adaptive filter.
The system output is used to control the adaptive filter and is an estimate of ***x(n)***. Provided ***x(n)*** is uncorrelated with ***v(n)***, and the adaptive filter is adjusted to give a system output ***y(n)*** that has the least possible energy, then ***y(n)*** is a best least-squares fit to the clean signal ***x(n)***.

## III. Simulation and Results

The primary objective of this Section was to explain how to use Non-recurrent and recurrent networks that represent the Adaptive filter to achieve Adaptive noise canceller(ANC).

### 1.Adaptive Noise Cancellation by Non-Recurrent network

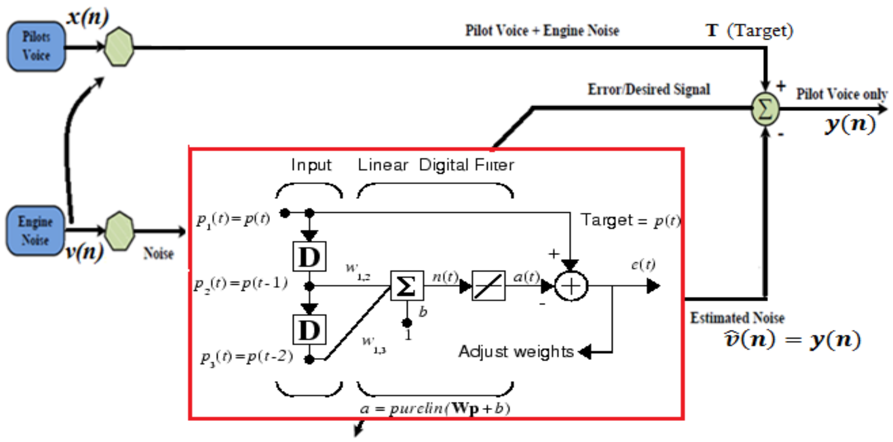


Fig.2.System ofnoise cancellationby non-recurrent network

A linear neuron is allowed to adapt so that given one signal, it can predict a second signal.
In figure (3) (TIME) defines the time steps of this simulation. **P** defines a signal over these time steps. **T** is a signal derived from **P** by shifting it to the left, multiplying it by **2** and adding it to itself.

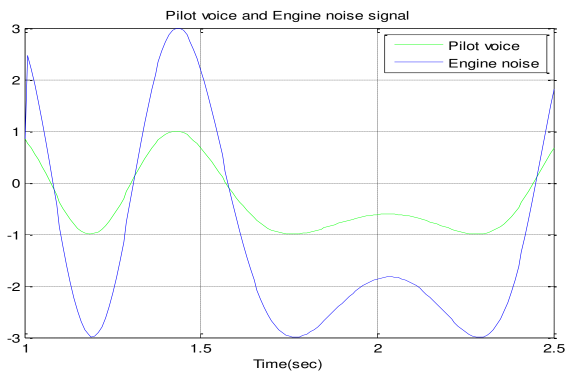


Fig.3.Primaryinput and target signals

The linear network must have tapped delay in order to learn the time-shifted correlation between **P** and **T**. NEWLIN creates a linear layer.**[-3 3]** is the expected input range. The second argument is the number of neurons in the layer is 1. **[0 1]** specifies one input with no delay and one input with a delay of one. The last argument is the learning rate is 0.1 .
ADAPT simulates adaptive networks. It takes a network, a signal, and a target signal, and filters the signal adaptively. Plot the output **Y** in blue, the target T in green and the error E in red. By t=1.54 the network has learned the relationship between the input and the target and the error drops to near zero, see figure (4).

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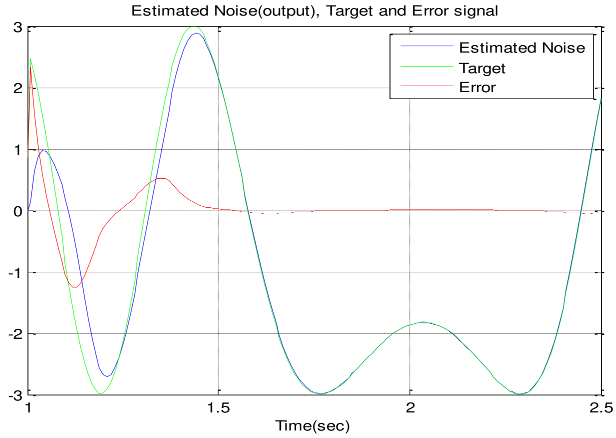


Fig.4.Relationship between the output and the target and the error

## 2. Adaptive Noise Cancellation by Recurrent Network

The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. A NARX is allowed to adapt so that given one signal, it can predict a second signal.

*a) General Structure of NARX Network*

The architectural layout of a recurrent network takes many different forms. In this section we describe only the input-output recurrent model.

*b) Input-output recurrent model*

Figure (5)shows the architecture of a generic recurrent network that follows naturally from a multilayer perceptron (BPNN). The model has a single input that is applied to a tapped -delay-line memory of $q$ units. It has a single output that is fed back to the input via another tapped delay-line memory also of $q$ units. The contents of these two tapped-delay-line memories are used to feed the input layer of the multilayer perceptron.The present value of the model input is denoted by **v(k)**,and the corresponding value of the model output is denoted by **y(k+1)**;that is,the output is ahead of the input by one time unit.Thus, the single vector applied to the input layer of the multilayer perceptron consists of a data window made up as follows:

- Present and past values of the input, namely

  $\boldsymbol{v(k), v(k-1), \ldots, v(k-q+1)}$(2)

Whichrepresent external inputs originating from outside the network.

- Delayed values of the output,namely,

$$\boldsymbol{y(k), y(k-1), \ldots, y(k-q1)} \qquad (3)$$

On which the model output y(k+1) is feedback.

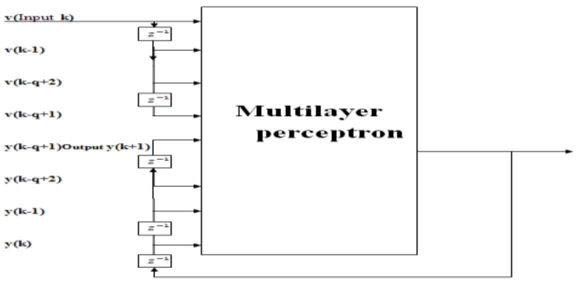


Fig.5.Nonlinear autoregressive with exogenous inputs NARXmodel

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Thus the recurrent network of Figure (5)is referred toas nonlinear autoregressive with exogenous inputs(NARX) model[12].
The dynamic behaviour of the NARX model is described by

$$\boldsymbol{y}(\boldsymbol{k}+\mathbf{1}) = \boldsymbol{F}(\boldsymbol{y}(\boldsymbol{k}), \ldots, \boldsymbol{y}(\boldsymbol{k}-\boldsymbol{q}+\mathbf{1}), \boldsymbol{v}(\boldsymbol{k}), \ldots, \boldsymbol{v}(\boldsymbol{k}-\boldsymbol{q}+\mathbf{1})) \qquad (4)$$

The nonlinear mapping is generally unknown and can be approximated by a standard multilayer perceptron (MLP) network.
We have the choice of basing the prediction signal procedure on input-output recurrent model as following:
Let $\boldsymbol{y}(\boldsymbol{k})$ denote the output of the system due to the input $\boldsymbol{v}(\boldsymbol{k})$ for varying discrete time $\mathbf{k}$ .Then, choosing to work with the NARX model.
The prediction signal takes the form:

$$\hat{\boldsymbol{y}}(\boldsymbol{k}+\mathbf{1}) = \boldsymbol{\varphi}(\boldsymbol{y}(\boldsymbol{k}), \ldots, \boldsymbol{y}(\boldsymbol{k}-\boldsymbol{q}+\mathbf{1}), \boldsymbol{u}(\boldsymbol{k}), \ldots, \boldsymbol{u}(\boldsymbol{k}-\boldsymbol{q}+\mathbf{1})) \qquad (5)$$

Where $\boldsymbol{q}$:is the order of the unknown systemAt time $\boldsymbol{k}+\mathbf{1}$, the $\boldsymbol{q}$ past values of the input and the $\boldsymbol{q}$past values of the output are available.
The model output $\hat{\boldsymbol{y}}(\boldsymbol{k}+\mathbf{1})$represents an estimate of the actual output$\boldsymbol{y}(\boldsymbol{k}+\mathbf{1})$.The estimate $\hat{\boldsymbol{y}}(\boldsymbol{k}+\mathbf{1})$ is subtracted from$\boldsymbol{y}(\boldsymbol{k}+\mathbf{1})$to produce the error signal.

$$\boldsymbol{e} = \boldsymbol{y}(\boldsymbol{k}+\mathbf{1}) - \hat{\boldsymbol{y}}(\boldsymbol{k}+\mathbf{1}) \qquad (6)$$

Where$\boldsymbol{y}(\boldsymbol{k}+\mathbf{1})$ plays the role of desired response. The error $\boldsymbol{e}(\boldsymbol{k}+\mathbf{1})$is used to adjust the synaptic weights of the neural network so as to minimize the error in some statistical sense.
The performance accuracy of the NARX model is given by the root mean square (RMS) value of the error $\boldsymbol{e}(\boldsymbol{k}+\mathbf{1})$.
There is an important configuration that is useful in training of the NARX network needs explanation. We can consider the output of the NARX network to be an estimate of the output of some nonlinear dynamic system that we are trying to model. In Parallel architecture, the output is feedback to the input of the feed-forward neural network as part of the standard NARX architecture, as shown in the Figure (6). Because the true output is available during the training of the network, we could create a series-parallel architecture [12] in which the true output is used instead of feeding back the estimated output, as shown in the Figure (7). This has two advantages. The first is that the input to the feed-forward network is more accurate. The second is that the resulting network has a purely feed-forward architecture, and static back-propagation can be used for training.

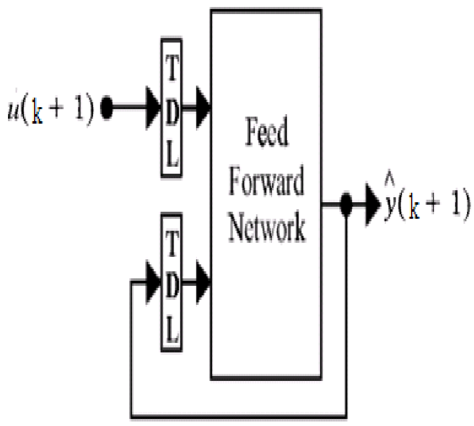

Fig.6. Parallel Architecture

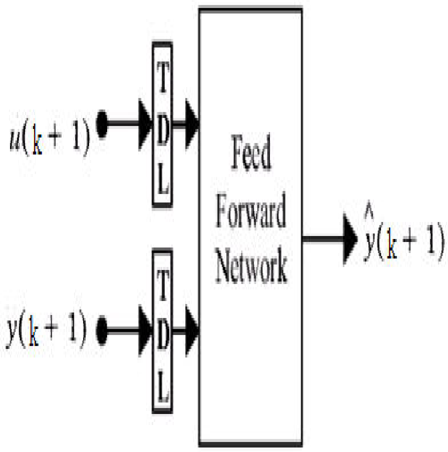

Fig.7.Series-Parallel Architecture

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Figure (8) shows the NARX solution for the prediction signal problem.

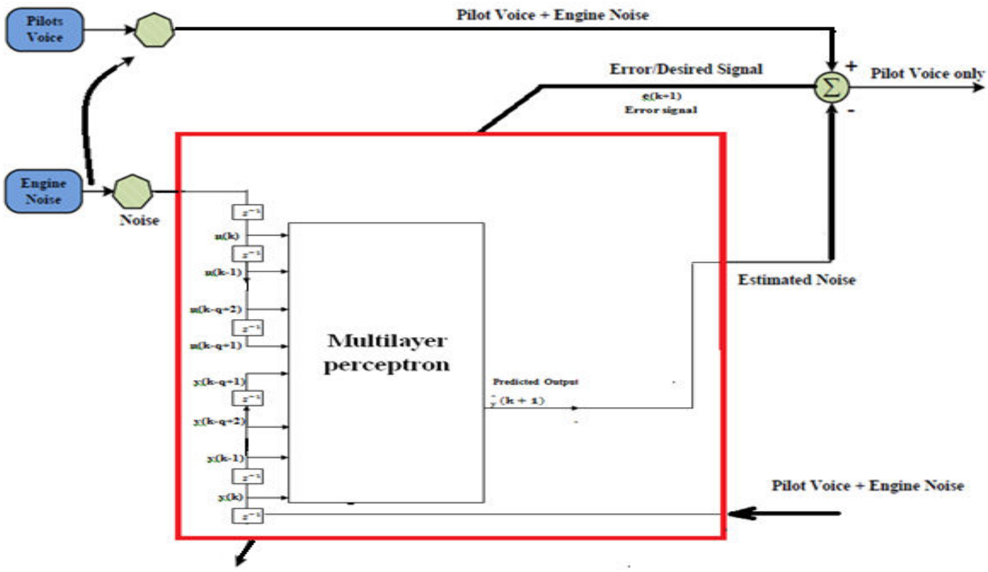

Fig. 8. The NARX solution for the prediction signal problem.

Using prediction signal procedure described in the section (2), we can infer a NARX networkfor theAdaptive Noise Cancellation.
The input-output training data samples are obtained at a sampling time **Δ*T*=0.01sec** to form two time series. Figure (9)shows engine noise signal **v(t)** applied to the NARX network and the Figure (10)shows the pilot's voice signal ***x*(t).**

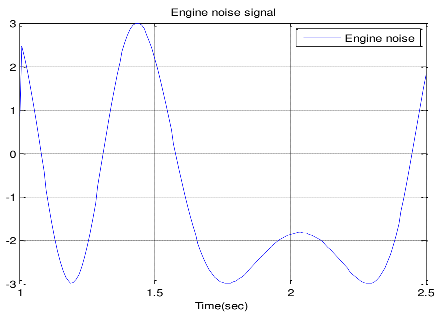

Fig.9.Engine noise signal

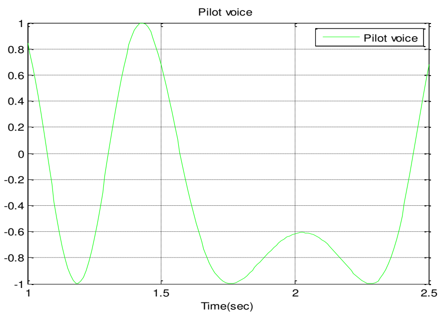

Fig.10.Pilot's voice signal

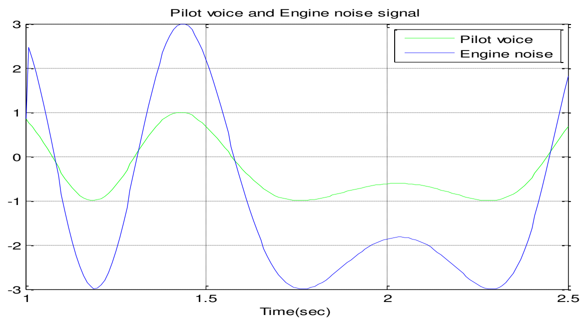

Fig.11.: Pilot's voice andEngine noise signal

First, load the training data. Second use tapped delay lines with two delays for both the input and the output, so training begins with the third data points. There are two inputs to the series-parallel network, the **u(t)** sequence and the **y(t)** sequence, so **p** is a cell array with two rows.

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Create the series-parallel NARX network using the function narxnet. Use one neuron in the hidden layer and use trainman for the training function, and then prepare the data.
Notice that the **y(t)** sequence is considered as feedback signal, which is an input and also an output (target). Later, when the loop is closed, the appropriate output will be connected to the appropriate input. Nowthe network is ready to be trained.
The networkhas been simulated and presented the resulting errors for the series-parallel implementation.
The result is displayed in figure (12). One can see that the errors are very small. However, because of the series-parallel configuration, these are error for only a one-step-ahead prediction. A more stringent test would be to rearrange the network into the original parallel form (closed loop) and then to perform an iterated prediction over many time steps.

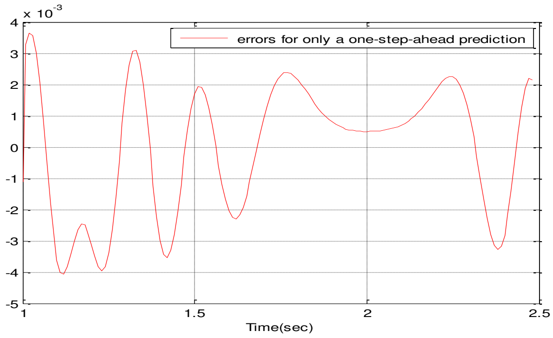


Fig.12.: Errors for only a one-step-ahead prediction

There is a toolbox function (closed loop) for converting NARX and other networks from the series-parallel configuration (open loop), which is useful for training, to the parallel configuration (closed loop), which is useful for multi-step-ahead prediction testing.

By using the closed-loop (parallel) configuration, an iterated prediction of 140time stepsare done. The two initial inputs and the two initial outputs are needed to be loaded with initial conditions. One can use the prepared function to prepare the data. It will use the network structure to determine how to divide and shift the data appropriately.
The following figure illustrates the iterated prediction.Plot the output Estimated Noise in blue, the Target T in green and the Error E in red. The general behavior of the NARX model (output Estimated Noise) is very accurate to the behavior of the actual engine noise.

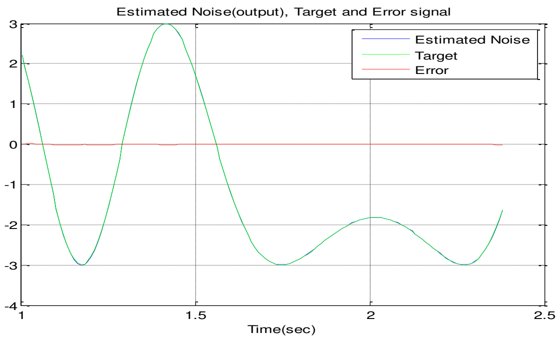


Fig.13.Comparison between output signal and target

In order for the parallel response iterated prediction to be accurate, it is important that the network be trained so that the errors in theseries-parallel configuration (one-step-ahead prediction) are very small.

### 3. Comparison between the Non-recurrent and recurrent networks

Practically, the dynamic performance accuracy of Adaptive noise canceller(ANC) is given by measures the mean square value of the error e(k) and the time steps as depicted in Table (1).

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**Table.1: Comparison between the non-recurrent and recurrent networks.**

| Adaptive filter | Time(sec) | RMS |
|---|---|---|
| Non-recurrent neural network | 1.2513 | 0.3972 |
| Recurrent neural network | 20.9471 | 0.0071 |

Results show that each technique has its own advantages and drawbacks when the processing time is the issue; the non-recurrent neural network gives better performance.
On the other hand, when it comes to accuracy the recurrent neural network technique shows better accuracy.

## IV. CONCLUSIONS

In this paper both Recurrent Neural Network and Non-Recurrent Neural Network by the same number of neural in hidden layer are used as an adaptive filter in order to make an effective noise cancellation.Adaptive Noise Cancellation is an alternative way of cancelling noise present in a corrupted signal. The principal advantages of the method are its adaptive capability, its low output noise, and its low signal distortion.As a result of the simulation the Non-Recurrent Neural Network technique processes the data faster than the Recurrent Neural Network technique in terms of time.However, the Recurrent Neural Network is more accurate than the Non-Recurrent Neural Network when the Root Mean Square (RMS) is used.To sum up, a designer has a variety of options to come up with the perfect approach depending on the application.

## REFERENCES

1. Konar, Amit, Artificial intelligence andsoft computing, CRC Press LLC ISBN 0-8493-1385-6,2000.
2. A. Rubaai and R. Kotaru, “Online identification and control of a DC motor using learning adaptation of neural networks,” IEEE Trans. Industry Application, Vol. 36, 2000, pp. 935-942
3. Hagan, M.T., H.B. Demuth, and M.H. Beale, Neural Network Design, Boston, MA: PWS Publishing, 1996.
4. Rosenblatt, F., Principles of Neurodynamics, Washington, D.C.: Spartan Press, 1961.
5. Widrow, B., and S.D. Sterns, Adaptive Signal Processing, New York, Prentice-Hall, 1985.
6. K.J. Hunt, D. Sbarbaro, R. Zbikowski and P.J. Gawthrop, “Neural networks for control systems: A survey,” Automatica, Vol. 28, No. 6, 1992, pp. 1083-1112,1992.
7. Dennis, J.E., and R.B. Schnabel, Numerical Methods for Unconstrained Optimization and Nonlinear Equations, Englewood Cliffs, NJ: Prentice-Hall, 1983.
8. M. T. Hagan, O. D. Jesus, R. Schultz, Training Recurrent Networks for Filtering and Control, in (editors) L.R. Medsker, L.C. Jain, Recurrent Neural Networks – Design and Applications, CRC Press, 2001
9. D.P. Mandic, J.A. Chambers, Recurrent Neural Networks for Prediction, JohnWiley&Sons, 2001
10. H.B. Demuth, M. Beale, Users’ Guide for the Neural Network Toolbox for Matlab, The Mathworks, Natica, MA, 1998
11. Parks, T.W., and C.S. Burrus, Digital Filter Design, John Wiley & Sons, 1987, pp.226-228.
12. Haykin, S. Adaptive Filter Theory. 3rd ed. Englewood Cliffs, NJ: Prentice Hall, 1996
13. Joseph j.Distefano, Ivan J.Williams,’’Feedback and control systems’’ 2nd edition; Mcgraw-Hill Companies,1990.
14. Dorf R.C. and Bishop R.H., “Modern Control System”, Addison WesleyLogman, Inc., 1998.
15. Hagan, M.T., and M. Menhaj, "Training feed-forward networks with the Marquardt algorithm," IEEE Transactions on Neural Networks, No. 6, 1999, pp. 989-993, 1994.
16. prof. Mustafa Alfellany - Comparison between the non-recurrent and recurrent networks. .COET/BANI-WALID.206
17. EUGEN DIACONESCU, The use of NARX Neural Networks to predict Chaotic Time Series. Electronics, Communications and Computer Science FacultyUniversity of Pitesti Targu din Vale, Nr. 1ROMANIA .eugend@upit.ro

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|| Volume 11, Issue 2, February 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1102002 |

18. prof. Ali A. Hassan - Artificial neural networks for Identification of nonlinear industrial processes. AUFOEE.2000.
19. Jos_e Maria P. J_unior and Guilherme A. Long-Term Time Series Prediction with the NARX Network: An Empirical Evaluation.BarretoDepartment of Teleinformatics EngineeringFederal University of Cear_a, Av. Mister Hull, S/N CP 6005, CEP 60455-760, Fortaleza-CE, Braziljosemenezesjr@gmail.com, guilherme@deti.ufc.br
20. Language of technical computingversion 7.5 .0.342(R2007b)
21. Prof. Robert Morley ,Digital Active Noise Cancelling Headphones By Michael Jezierny Brenton Keller Kyung Yul Lee

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