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Intelligent Noise Cancellation Using Adaptive RNN-Based Filtering

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إلغاء الضوضاء الذكي باستخدام التصفية التكيفية القائمة على شبكة RNN

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Abstract: This study details the design and implementation of an Adaptive Noise Canceller (ANC) using a Recurrent Neural Network (RNN), especially a Nonlinear Autoregressive model with exogenous inputs (NARX). The suggested approach is designed to efficiently remove non-stationary and colored noise from voice signals, a prevalent issue in settings like airplane cockpits. The dynamic recurrent architecture of the NARX network facilitates the improved modelling of intricate noise patterns for precise prediction and cancellation. The process was modelled in MATLAB/Simulink, showing that the RNN-based adaptive filter attains superior noise suppression, as shown by a low Root Mean Square (RMS) error. This method has been compared with the standard method. The findings validate that the recurrent network methodology provides outstanding accuracy, rendering it especially appropriate for applications where precision in noise cancellation is paramount, albeit it requires extended computational processing time.

Keywords: adaptive filter, dynamic neural network, NARX

الملخص:

تفصل هذه الدراسة تصميم وتنفيذ جهاز إلغاء الضوضاء التكيفي (ANC) باستخدام شبكة عصبية متكررة (RNN)، وخاصة نموذج التراجع الذاتي غير الخطي مع مدخلات خارجية (NARX). تم تصميم النهج المقترح لإزالة الضوضاء غير الثابتة والملونة من إشارات الصوت بكفاءة، وهي مشكلة شائعة في أماكن مثل قمرة قيادة الطائرات. تسهل البنية المتكررة الديناميكية لشبكة NARX تحسين نمذجة أنماط الضوضاء المعقدة من أجل التنبؤ والإلغاء الدقيقين. تم نمذجة العملية في MATLAB/Simulink، مما أظهر أن المرشح التكيفي القائم على RNN يحقق قمعًا فائقًا للضوضاء، كما يتضح من انخفاض خطأ الجذر المتوسط المربع (RMS). هذه الطارق تم مقارنتها بالطريقة التقليدية. تؤكد النتائج أن منهجية الشبكة المتكررة توفر دقة فائقة، مما يجعلها مناسبة بشكل خاص للتطبيقات التي تتطلب دقة قصوى في إلغاء الضوضاء، على الرغم من أنها تتطلب وقتًا أطول للمعالجة الحسابية.

الكلمات المفتاحية: مرشح تكيفي، شبكة عصبية ديناميكية، NARX

Additive random noise degrades the quality of sound signals used for speech interaction in noisy environments, such as those created by moving automobiles, trains, aeroplanes, or a crowded telephone line. It is better to remove the noise from the original signal as it is an unwanted signal. If you want your noise cancellation system to work, you need to check it often since noise is stochastic and changes all the time. There are a lot of ways to get rid of noise, however using adaptive filters is the best way to get rid of noise completely.

Everyday life is filled with aural noise, whether you're talking on a noisy phone line, using a mobile phone in a moving car, train or aircraft, or any number of other situations. This background noise introduces environmental interference that distorts the original signal carrying the information.

For the sake of effective communication, this background noise must be removed [1].

To separate the intended signal from the polluted one, one must make an estimate at each time since noise is a stochastic process. Adaptive filters are often used to cancel out background noise in non-stationary, noisy, and dynamical environments. Two inputs are necessary for adaptive filters.

- Acoustic disturbance
- Principal signal + Acoustic disturbance

Although there are several adaptive filters and their applications described in the literature, the most popular one is the one developed by Widrow and Hoff. It utilises the Least Mean Square (LMS) algorithm.

The robustness, excellent tracking capabilities, and simplicity of the LMS in terms of computational needs and ease of implementation are the main reasons for its adoption. An FIR filter and an equation for updating weights at the first order are used to carry it out. It has so found usefulness in a wide variety of contexts [4].

II - Design of Adaptive Noise Canceller

This study uses the following case studies to build the system and implement an Adaptive Noise Canceller (ANC).

The pilot's speech is muffled by the roar of the plane's engines. Assume for the sake of argument that x(n) is the pilot's voice, which is the desired signal.

To record the noises made by the engine, a microphone is placed next to it. The noise is represented by v(n). The noises of the engine and the pilot's voice may be captured by a second microphone placed beside the pilot.

The goal of our technology is to isolate the pilot's voice from engine noise and output just the filtered signal.

Minimising the mean square error between the desired output and the filter output is the basic principle upon which an adaptive filter functions. The adaptive filter's weights change to decrease error and achieve the target output. Performance in different contexts is affected by the fact that different adaptive filters use different criteria for minimisation of errors.

Both single-input and multi-input versions of adaptive filters are possible. Filtration technologies that may be either linear or nonlinear Choose between FIR or IIR filters. Active Noise Cancellation (ANC) is implemented using IIR filters in this article. The reliability and relative ease of adaptability of these filters make them widely utilised. Since the pilot's microphone picks up different noise than the reference microphone, it is not possible to simply remove the engine noise from the pilot's microphone. No correlation exists between these two signals. Delayed responses and changes in volume are seen. Not to mention that these differences may be altered. They shift based on a number of factors, including the passage of time and the location of the pilot's microphone in relation to the engine of the aircraft. In its most basic form, noise is a constantly changing stochastic process. In real time, the pilot's audio stream is evaluated for noise and silenced accordingly.

Therefore, the desired results would not be achieved by building the permanent filter to carry out the operation. For this application, an adaptive filter is necessary.

Adaptive filters treat engine noise to equalise it with the noise polluting the voice stream. The noise is removed from the noisy signal to get a noise-free speech signal. In scenarios involving a communications system receiver, when immediate values of contaminating noise are inaccessible and only a noisy signal is present, total noise cancellation is unattainable. Nonetheless, noise reduction may be accomplished in a general sense by using the statistics of the signal and the noise process in such instances [1]. The noise cancelling method is used as shown in figure (1):

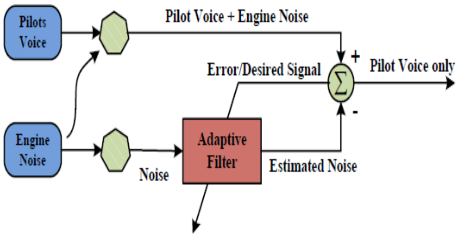

Figure 1. Noise cancellation system

The influence of engine noise on the pilot's voice was removed using Least Mean Squares (LMS) adaptive filtering.

Figure 1 illustrates the core principles of adaptive noise reduction. The adaptive filter receives the combustion noise signal v(n) as input, which is independent with the pilot's voice signal x(n). The starting signal v(n) undergoes processing through an adaptive filter in order to produce an output that predicts the noise v(n).

The device's output y(n) is obtained by subtracting the output from the distorted signal (x(n) + v(n)). This is occasionally termed an error signal. The error functions as information for the adaptable algorithm module. The error signal functions as the "target signal" for the disturbance canceller, leading to the device's output. The signal is mathematically defined by equation (1).

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

In this context, DS denotes the desired signal, whereas y(n) represents the result of the dynamic filter, which acts as an estimate of the input noise to the adaptive filter.

The system output regulates the parameters of the adaptive filter and yields an approximate value of x(n). If x(n) is uncorrelated with v(n), and the adaptive filter aims to minimise the magnitude of the system's output y(n), then y(n) reflects the optimal least-squares approximation of the initial signal x(n).

Section III - Modelling and Results

This section aims to clarify the application of recurrent networks incorporating the Adaptive filter for the implementation of Adaptive Acoustic Cancelling (ANC). The irregular regressive system with an external input (NARX) is a continually evolving network distinguished by feedback connections that encompass various stages of the network. A NARX model is allowed to adapt to predict an additional signal upon a specified primary signal

.Input-output recurrent model

The total structure of NARX systems exhibits considerable diversity. This section addresses the input-output portion of the recurrent model.

Figure (2) illustrates a broader recurrent network (BPNN), which is an architectural derivative of the multiple-layer perceptron concept. A tapped-delay-line memory consisting of q units processes the model's singular input. The system receives q units of input and produces a single output through a secondary tapped delay-line memory. The multilayer perceptron receives input from two tapped-delay-line memories. In this framework, v(k) denotes the present value of the input, while y(k+1) signifies the corresponding value of the output, indicating that the result is only one unit subsequent to the input. Multilayer perceptrons utilise a data window comprising a number of components as a singular vector input to the input layer: Current and previous amounts for the input, specifically

$$v(k), v(k-1), \ldots, v(k-q+1) \qquad (2)$$

Which stand for data coming from sources outside the network.

- ● Postponed parameters of the result, specifically,

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

The system's outcome y(k+1) serves as correction.

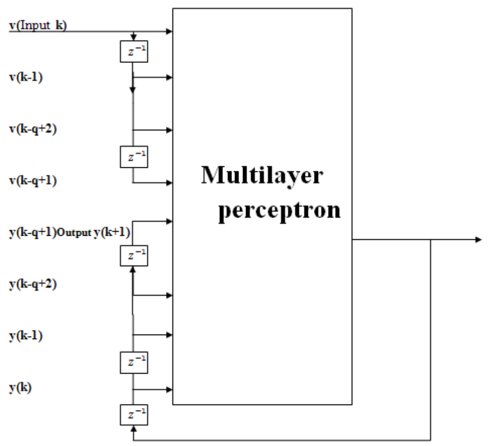

Figure 2. Nonstandard self-correcting model with exogenous inputs NARX model

Therefore, the Nonstandard self-correcting model with exogenous inputs NARX model is the name given to the recurrent network in Figure (2). [12].

The dynamic behavior of the NARX model is described by

$$y(k+1) = F(y(k), \dots, y(k-q+1), v(k), \dots, v(k-q+1)) \qquad (4)$$

A typical multilayer perceptron (MLP) network may be used to mimic the nonlinear mapping, which is often unknown.

We may choose to use the input-output recurrent model as the foundation for the prediction signal method in the manner described below:

For variable discrete time k, let y(k) represent the output generated by the system the input v(k). Next, deciding to use the NARX model.

The anticipated message is expressed as:

$$\hat{y}(k+1) = \varphi\big(y(k), \dots\dots, y(k-q+1), u(k), \dots\dots, u(k-q+1)\big) \qquad (5)$$

In this context, q: represents the unknown order of the system. At the moment k+1, we've got the ability to use the data entering and results from the previous q instances.

It is estimated that the real output y(k+1) will be equal to or more than The result of the simulation y<(k+1). A subtraction of the estimate y ̂(k+1) from y(k+1) yields the error signal.

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

Where y(k+1)) functions as the intended response. The error e(k+1) is employed to adjust the weights of synaptic neurones of the neural network, aiming to minimise the error within a statistical framework.

The computational precision of the NARX model is indicated by the inverse root mean square (RMS) measurement of the error e(k+1). A crucial configuration pertinent to the training provided by the NARX system necessitates clarification. The NARX network's output serves as a projection of the output of the nonlinear dynamic system under consideration. In concurrent structure, the output is returned to the starting point of the fed-forward neural network, thus aligning with the conventional NARX architecture, as depicted in Figure 3. Considering that the true result is available during the training of the network, a parallel series architecture can be implemented [12], employing the true output for feedback instead of the estimated output, as demonstrated in Figure 4. This offers two benefits. The primary observation is that the data fed to the fed-forward system demonstrates enhanced accuracy. Another benefit is that the net that results has a strictly feed-forward structure, enabling the use of fixed replication during training

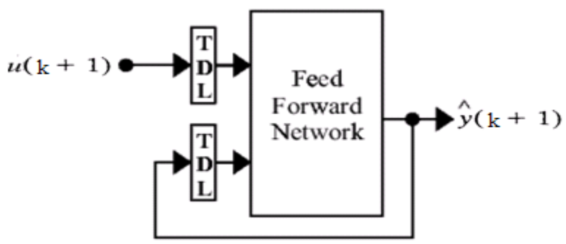

Figure 3. Parallel Architecture

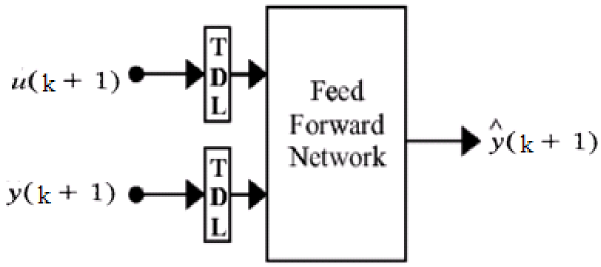

Figure 4. Series-Parallel Architecture

Figure (5) presents the NARX approach for the forecasting communication problem..

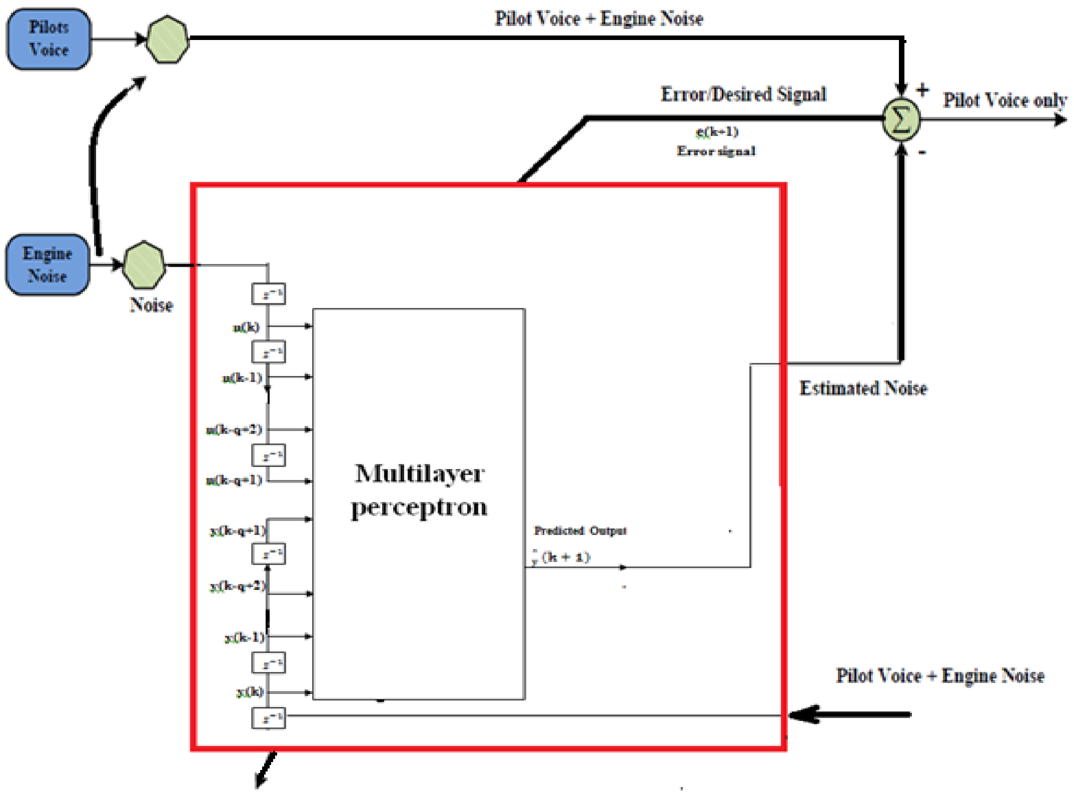

Figure 5. The NARX Framework tackles the challenge of signal estimation.

By employing the forecasting signal processing technique described, we can derive a NARX system for Flexible Signal Removal.

The output and input training set samples are gathered at an average period of $\Delta T = 0.01$ seconds to generate two time series. Speech signal denoted as x(t).

Figure 6 presents the combustion noise signal v(t) utilised in the NARX system, while Figure 7 shows the pilot's

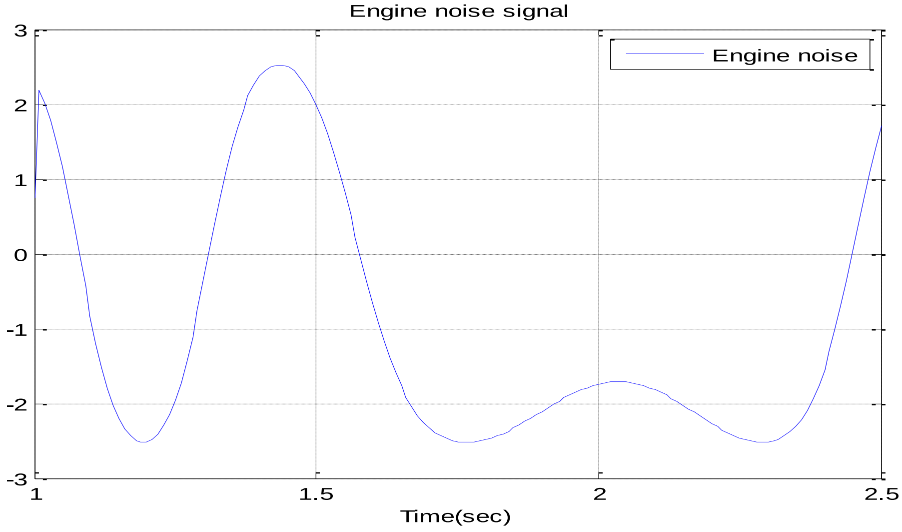

Figure 6. Engine noise signal

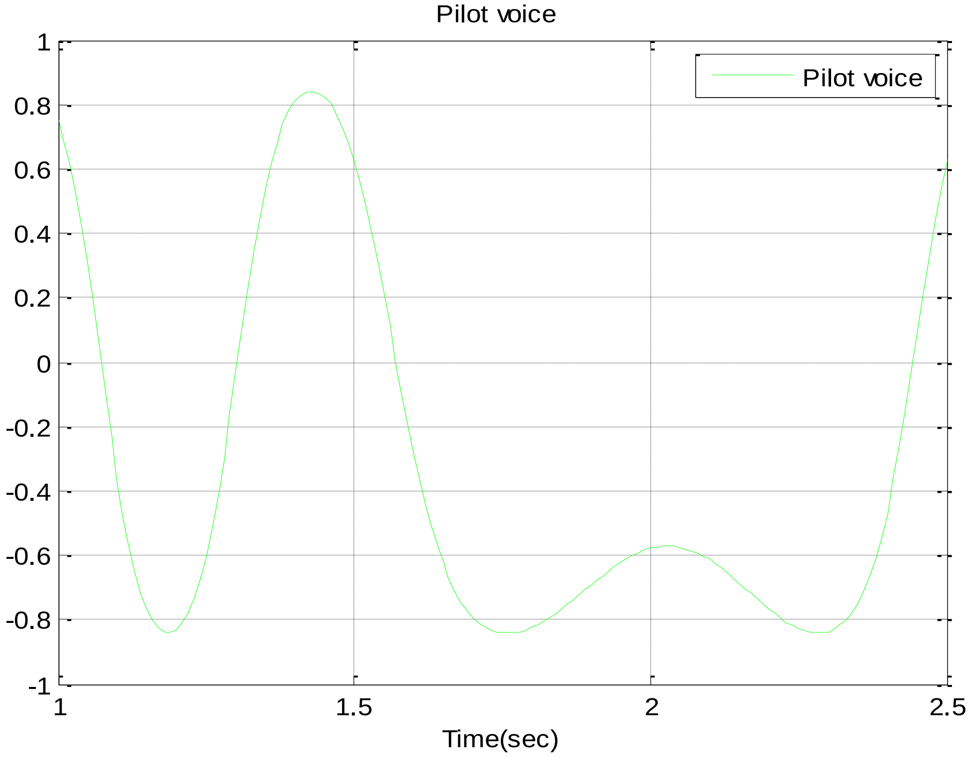

Figure 7. Pilot's voice signal

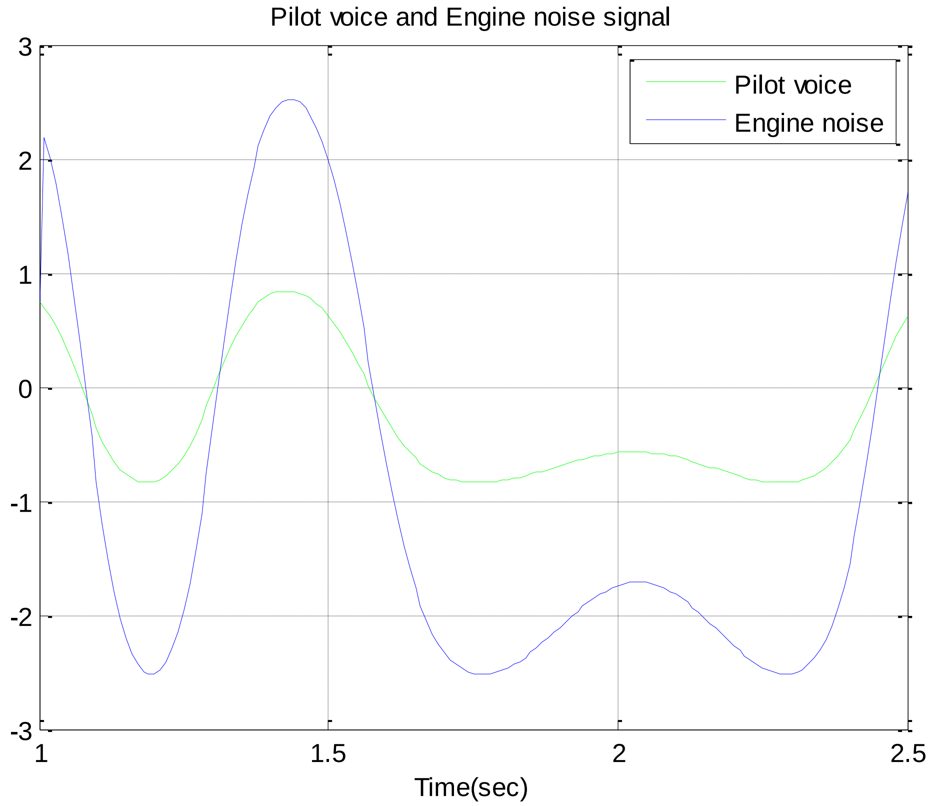

Figure 8. Pilot's voice and Engine noise signal

Commence with the loading of the training data. The second implementation employs tapped delay lines with simultaneous pauses for input as well as output, leading to the commencement of learning to the third data point. The series-parallel network comprises two inputs, which are the u(t) pattern and the y(t) sequence. Thus, p is organised as an individual cell array with two rows.

Employ the narxnet method to develop the sequential parallel NARX network. Employ one neurone in the beneath layer and apply repetition as the training task. Set up the data as needed.

The y(t) pattern is recognised as a response signal, operating concurrently as either a source of data and a result (target). Upon completion of the cycle, the specified outcome will be connected to the appropriate input. The system is now ready for training.

The network simulation was conducted, and the mistakes made for the series-parallel execution have been documented.

Figure 9 illustrates the outcome. The detected errors are negligible in magnitude. Nonetheless, because of the parallel series arrangement, these errors are relevant solely for a forward-looking forecast. A more thorough assessment entails reorganising the system into its initial concurrent arrangement (closed circle) and then performing an iterative prediction over several time steps.

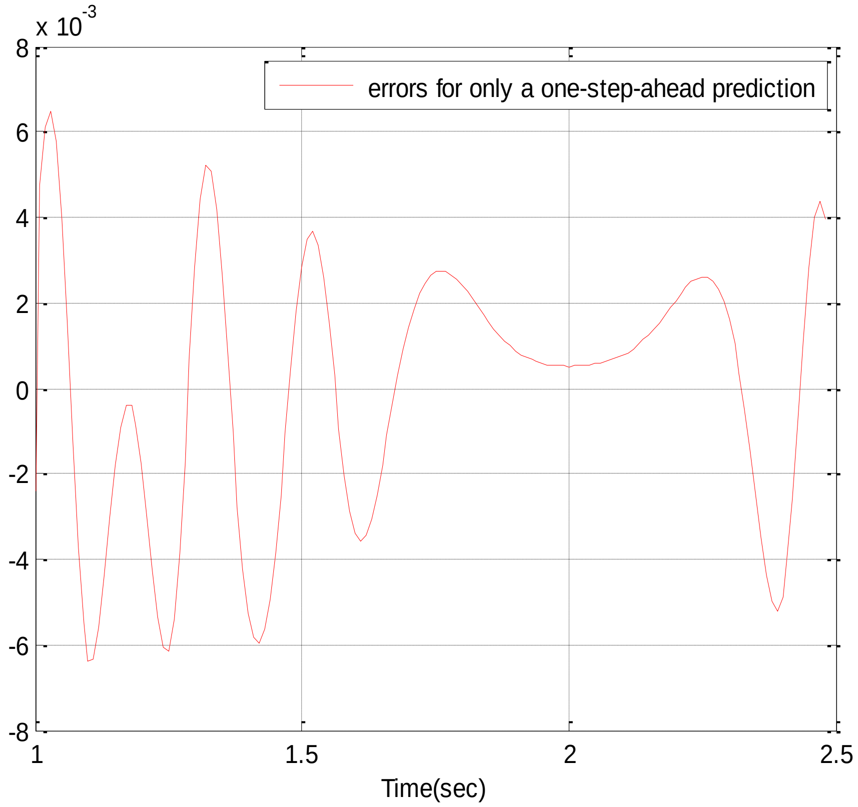

Figure 9. Errors for only a one-step-ahead prediction

A toolbox function facilitates the conversion of NARX and additional algorithms from a parallel-series arrangement (an open loop), advantageous for training purposes, to a parallel arrangement ("closed") loop), which is useful for multiple-stage forecasting testing.

The sealed-loop (parallel) arrangement enables a continuous forecasting process across 140 time steps. Both of the startling inputs as well as the two initial results must incorporate initial conditions. The generated function can be employed for preparing the data. The framework of the network will be used to determine the suitable partitioning and movement of the data.

The following figure illustrates the technique of repeated forecasting. Present the output for Estimated Noise utilising a blue hue design, with the goal T in the green colour, and the resultant error E in red. The general behaviour of the NARX model, particularly the result of predicted Noise, more closely corresponds with the actual behaviour of engine noise.

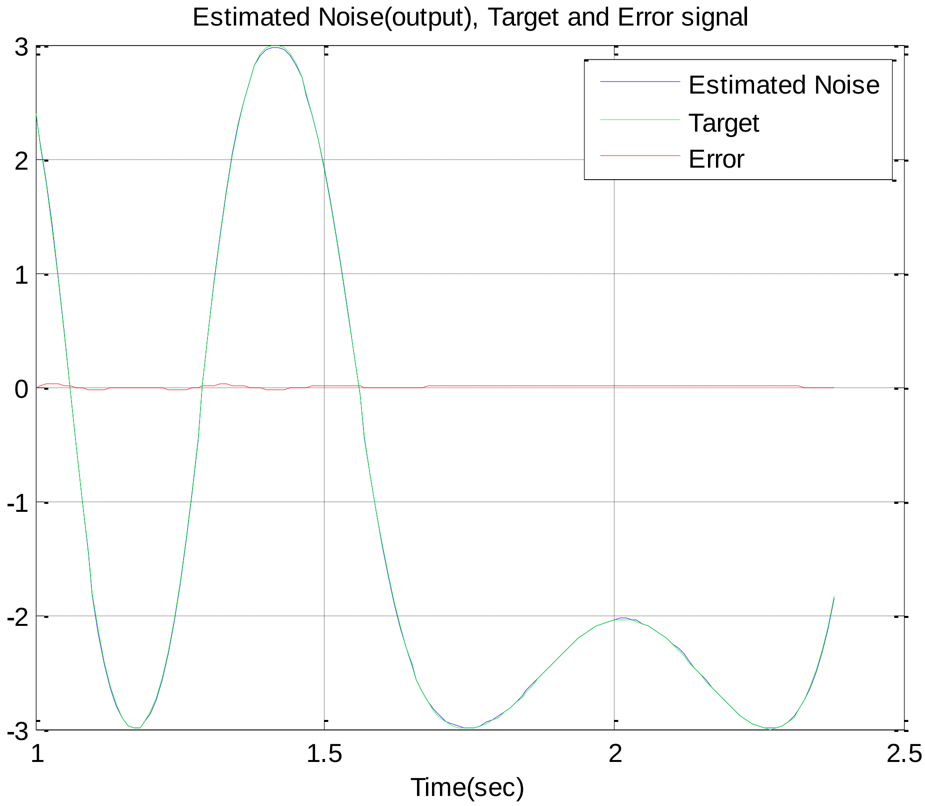

Figure 10. Estimated Noise (output), Target and Error signal

To guarantee the precision in the sequential reaction to repeated forecast, the network has to be trained to minimise deviations in the parallel series arrangement (one-step-ahead prediction).

The dynamical precision of an intelligent noise cancellation (ANC) is assessed by evaluating the average squared value of the variance e(k) alongside the duration of the stages, as illustrated in Table 1.

Table.1 The performance of (ANC)

Adaptive filter	Time(sec)	RMS
Recurrent neural network	6.0474	0.0101

The findings show that the Recurrent Neural Network is very accurate when accuracy is the most important thing, although it takes longer to process.

The RNN-based technique provides enhanced accuracy in intricate noise situations, although with increased processing requirements. NARX networks surpass conventional filters in modelling complex noise patterns, particularly in the presence of colored or non-stationary noise. Real-Time Tradeoff: Conventional techniques such as LMS and RLS are favored for real-time applications owing to their simplicity and rapidity.

IV - Conclusions

This study effectively created and demonstrated an adaptable Sound Cancellation (ANC) utilising a recursive neural network (RNN), specifically a non-linear Autoregressive Model with External parameters (NARX) model. The simulation results clearly demonstrate the efficacy of this method in reducing complex, non-stationary noise, such as aeroplane engine disruption from voice signals.

This study's primary achievement is the application of the dynamic NARX network. memory, enabling it to model temporal correlations and anticipate noise components with exceptional precision. This was confirmed by MATLAB/Simulink simulations, where the system attained an exceptional degree of noise cancellation, as shown by a very low Root Mean Square (RMS) error.

The quest for high accuracy entails a distinct trade-off: the computational complexity of the recurrent network design leads to increased processing time. Consequently, the suggested RNN-based ANC is not a general remedy but is strongly advocated for scenarios where signal purity and cancellation precision are critical, even if it compromises computational speed. Illustrations include essential communication systems in aircraft, high-fidelity audio processing, and biological signal filtration.

For more enhancing of the noise applications, an artifital neural network (ANN) Methods can be applied or other algorithms like PSO or GA.

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