Evaluation of Neural Networks Performance in Active Cancellation of Acoustic Noise

Mehrshad Salmasi[1], Homayoun Mahdavi-Nasab[2]
1- Young Researchers and Elite Club, Najafabad Branch, Islamic Azad University, Najafabad, Isfahan, Iran
Email: m_salmasi@sel.iaun.ac.ir
2- Department of Electrical Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Isfahan, Iran
Email: mahdavinasab@iaun.ac.ir

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ABSTRACT
Active Noise Control (ANC) works on the principle of destructive interference between the primary disturbance field heard as undesired noise and the secondary field which is generated from control actuators. In the simplest system, the disturbance field can be a simple sine wave, and the secondary field is the same sine wave but 180 degrees out of phase. This research presents an investigation on the use of different types of neural networks in active noise control. Performance of the multilayer perceptron (MLP), Elman and generalized regression neural networks (GRNN) in active cancellation of acoustic noise signals is investigated and compared in this paper. Acoustic noise signals are selected from a Signal Processing Information Base (SPIB) database. In order to compare the networks appropriately, similar structures and similar training and test samples are deduced for neural networks. The simulation results show that MLP, GRNN, and Elman neural networks present proper performance in active cancellation of acoustic noise. It is concluded that Elman and MLP neural networks have better performance than GRNN in noise attenuation. It is demonstrated that designed ANC system achieve good noise reduction in low frequencies.

KEYWORDS: Generalized Regression Neural Network (GRNN), Elman Neural Network, MLP Neural Network, Active Noise Control (ANC), Feedback Active Noise Control System (FANC), SPIB Database.

1. INTRODUCTION

One of the most researched subjects in signal processing and acoustics is active noise control. This system uses microphones, sensors, and DSP boards to produce the anti-noise of an acoustic noise signal. Active noise cancellation (ANC) is a method for reducing undesired noise. ANC is achieved by introducing a canceling “anti-noise” wave through secondary sources. These secondary sources are interconnected through an electronic system using a specific signal processing algorithm for the particular cancellation scheme. If the original wave and the inverse of the original wave encounter at a junction at the same time, total cancellation occur. The challenges are to identify the original signal and generate the inverse without delay in all directions where noises interact and superimpose [1]-[3].

The traditional approach to acoustic noise control uses passive techniques such as silencers and barriers to attenuate the undesired noise. These passive silencers are valued for their high attenuation over a broad frequency range; however, they are relatively costly, large, and ineffective at low frequencies. On the other hand, the ANC system efficiently attenuates low-frequency noise where passive methods are either ineffective or tend to be bulky or very expensive. ANC is developing rapidly because it permits improvements in noise control, often with potential benefits in weight, size, size, volume, and cost. Blocking low frequency has the priority since most real life noises are below 1 KHz, for example engine noise or noise from aircrafts [1], [4].

Active control was first theorized by Paul Lueg in 1936 in a U.S. Patent. His patent describes measuring the sound field with a microphone and then feeding it to an electroacoustic secondary source. Seventeen years later, Olson and May published another paper which describes another system for active noise control. In contrast with Lueg’s paper which used prior knowledge of the signal from the detecting microphone (feed-forward control), Olson and May’s strategy needed no prior knowledge of the sound field. Instead, it used a feedback method to cancel sound by feeding back the signal from a much closer microphone to a second loudspeaker [2], [3].

Due to the lack of capable technology in the 1930’s and 1950’s, ANC was not possible until modern computers became available. The study of active noise control was

silent until 1975, when Kido first used digital techniques to achieve the precise balance required for feed-forward active control. In 1980, the well-known filtered-x least mean squares algorithm was developed by Morgan and also independently by Widrow in 1981 [1], [3]. For years, adaptive filters were the best choice for ANC systems. For nonlinear cases, neural networks show better performance than the adaptive filters [5].
There are a number of great applications for active noise cancellation devices. New developments in active noise control (ANC) have led to commercial products such as noise canceling headphones. One obvious application is that people working near aircraft or in noisy factories can now wear electronic noise cancellation headsets to protect their hearing [4], [6]. ANC is ideal for industrial use [7], [8]. The application of active noise reduction produced by engines has various benefits [9].
In this paper, two types of neural networks, feed-forward and recurrent, are designed for canceling acoustic noise. MLP neural network and GRNN are trained as feed-forward neural networks and Elman network is selected as a recurrent neural network. The main idea is to compare the performance of these networks in noise reduction of undesired noise. Acoustic noise signals are selected from SPIB database. The simulation results show that Elman and MLP neural networks have better performance in noise attenuation than GRNN.
In Section 2, an introduction to feedback ANC system is presented. The neural networks structure that is used in ANC is described in Section 3. Section 4 shows simulation results and finally, in Section 5 the conclusions of the research are discussed.

2. FEEDBACK ACTIVE NOISE CONTROL SYSTEM

The control system is fed with signals containing information about noise. These signals can be either advance signals that hold information of incoming noise, such as a reference signal, or signals that hold information about residual noise, such as an error signal. Not all control systems have a reference signal input. The control system with the reference input is called feed-forward and otherwise feedback controller. Depending on the application, both feedback control and feed-forward control can be used in active noise control [1], [4].
Structures for feed-forward ANC systems are classified into broadband feed-forward control with a reference sensor and narrow-band feed-forward control with a reference sensor that is not influenced by the control field (e.g. tachometer) [1], [4]. Figs 1, 2 and 3 show the broadband feed-forward, narrowband feed-forward and feedback ANC systems, respectively. A combination of the feed-forward and feedback control structures is called hybrid ANC system [1].

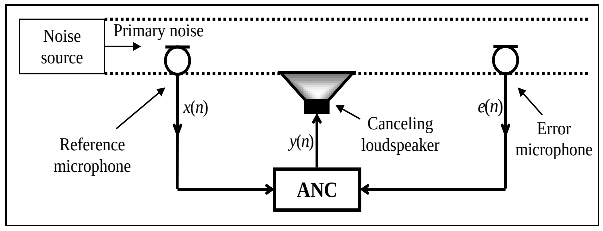

Fig. 1. Broadband feed-forward ANC system [1]

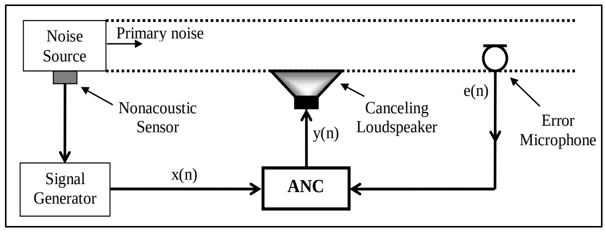

Fig. 2. Narrowband feed-forward ANC system [1]

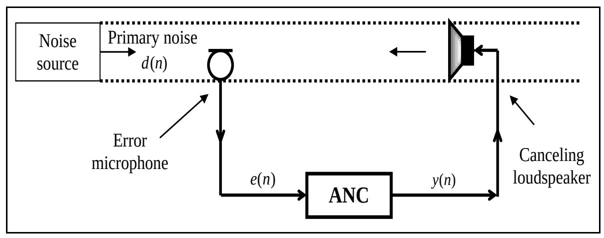

Fig. 3. Feedback ANC system [1]

A feedback ANC approach is taken in this research. The basic idea of an adaptive feedback ANC is to estimate the primary noise and use it as a reference signal x(n). According to block diagram depicted in Fig. 3, the error signal is obtained through the subtraction of primary noise, d(n), and generated inverse waveform, y(n); therefore assumed no information lost during the transition, the estimated primary noise d(n) could be regenerated by summation of error signal, e(n), and y(n). Since the reference signal comes from the estimated primary noise; therefore, the accuracy of the estimation determines the overall feedback mechanism performance [1], [10]. From Fig. 3, we can see that the primary noise can be expressed in the z-domain as,

$$D(z)=E(z)+S(z)Y(z) \tag{1}$$

Where E(z) is the residual error signal, Y(z) is the output of the adaptive filter and S(z) is the secondary path transfer function from y(n) to e(n). S(z) includes the digital-to-analog converter, reconstruction filter, power amplifier, loudspeaker, acoustic path from loudspeaker to error microphone, error microphone, pre-amplifier, anti-aliasing filter, and analog-to-digital converter [1]. The secondary path transfer function S(z) can be estimated as $\hat{S}(z)$. Thus, we can estimate the primary noise d(n) and use this as a synthesized reference signal x(n) as,

$$X(z) \equiv \hat{D}(z) = E(z) + \hat{S}(z)Y(z) \qquad (2)$$

A complete block diagram of the feedback ANC system is shown in Fig. 4 [1].

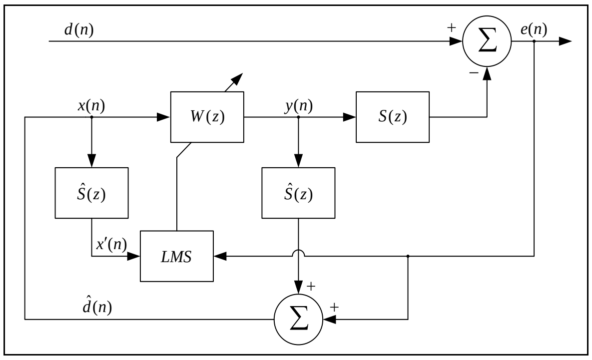

Fig. 4. Complete block diagram of feedback ANC system [1]

From Fig. 4, we can see that the reference signal x(n) and the secondary signal y(n) can be expressed as :,

$$x(n) \equiv \hat{d}(n) = e(n) + \sum_{m=0}^{M-1} \hat{s}_m \, y(n-m) \qquad (3)$$

$$y(n) = \sum_{l=0}^{L-1} w_l(n) x(n-l) \qquad (4)$$

[1,11].Where $\hat{s}_m$, m = 0, 1, . . . , M-1 is the M^{th} order FIR filter used to approximate the secondary path transfer function. $w_l(n)$, l = 0, 1, . . . , L-1 are the coefficients of the L^{th} order adaptive FIR filter W(z) at time n. These coefficients are updated by the FXLMS algorithm [11] as,

$$w_l(n+1) = w_l(n) + \mu x'(n-l) e(n) \qquad (5)$$

Where μ is the step size and $x'(n)$ is the filtered reference signal [11] and is given by,

$$x'(n) \equiv \sum_{m=0}^{M-1} \hat{s}_m \, x(n-m) \qquad (6)$$

From equation (1) and (2) it is concluded that $x(n) = d(n)$ if $\hat{S}(z) = S(z)$. Assuming that this condition is satisfied, then the adaptive feedback ANC system can be transformed into the feed-forward ANC system. If the LMS algorithm has slow convergence, i.e. the step size μ is small then the adaptive filter W(z) can be commuted with the secondary path transfer function S(z). Further, if we assume that the secondary path S(z) can be modeled as a pure delay, i.e. $S(z) = z^{-\Delta}$, then the feedback ANC system is equivalent to the standard adaptive predictor. So, the feedback ANC system acts as an adaptive predictor of the primary noise to minimize the residual error noise. It should be mentioned, when S(z) and $\hat{S}(z)$ are approximated by delays, they can be absorbed by W(z) [1].

In this paper, we use neural networks instead of adaptive filters for predicting future samples of noise. Fig. 5 shows the final block diagram of the predictor that we used in this research. Note that S(z) and $\hat{S}(z)$ are modeled as a pure delay, so $x(n) = d(n) = \hat{d}(n)$. In simulation procedures, the secondary path S(z) is assumed as a pure delay $S(z) = z^{-1}$.

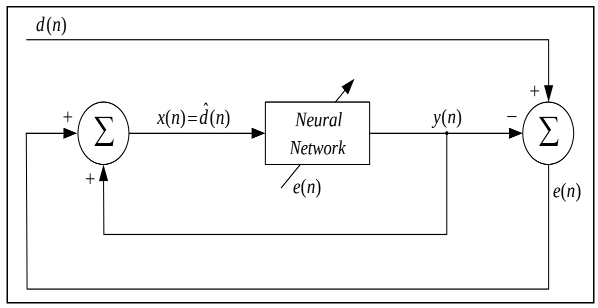

Fig. 5. Final block diagram of the predictor used in this research

3. NEURAL NETWORKS DESIGNING

As it was seen, we use a neural network as a predictor of the primary noise. Neural network accepts N samples as its input and then using these N samples for predicting the (N+1)'th sample. The predicted sample is the output of the neural network and is used for feeding the canceling loudspeaker. Loudspeaker generates a sample with the same amplitude and 180 degrees difference in phase. In this research, feed-forward and recurrent neural networks are used as a predictor. Multilayer perceptron and generalized regression neural networks are used as feed-forward networks and Elman network is selected as a recurrent neural network. In order to compare the networks appropriately, equal number of layers and neurons are considered for the networks.

Function approximation is one of the important applications of MLP neural networks [12], [13]. A two layer MLP network is designed and trained for ANC. The first layer transfer function is sigmoid and the second layer is linear. We experience various architectures for MLP neural network such as

NN(40,40,1), NN(10,10,1), … and deduced NN(20,20,1) as the best structure for ANC. Therefore, the designed network has 20 inputs, 20 neurons in its hidden layer and 1 neuron in its output layer.

A generalized regression neural network is often used for function approximation. It is one of the neural networks' types that can be used for prediction. It has a radial basis layer and a special linear layer. The GRNN has many advantages, but it suffers from one major disadvantage. It is slower to operate because it uses more computation than other kinds of networks to do its function approximation [13], [14]. The designed GRNN network is a two layer network. It has 20 inputs and 1 neuron in its output layer. The first layer has as many neurons as there are input vectors.

Recurrent neural networks are useful in temporal systems. We use Elman network as a recurrent neural network. The Elman network commonly is a two-layer back-propagation network with a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman networks to detect and generate time-varying patterns. The delay in the feedback connection stores values from the previous time step. These values can be used in the current time step [15]. The first layer which transfers function of designed network is sigmoid and the second layer is linear. The designed Elman network has the structure of NN(20,20,1).

MLP, GRNN and Elman neural networks structures are shown in Figs. 6, 7 and 8, respectively. The input to the networks is a tapped delay line (TDL) and is shown in Fig. 9. For training the networks, we use back-propagation algorithm and deduce Levenberg-Marquardt algorithm as the most efficient algorithm. For training the networks, acoustic noise samples are fed to the inputs of networks. The target is the sample that comes after the present 20 samples. So, the neural network is a predictor of d(n) from d(n-1), d(n-2), . . . , d(n-19), d(n-20).

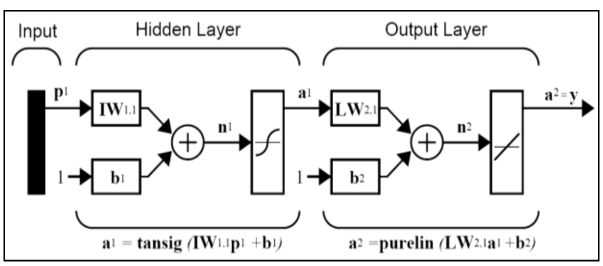

Fig. 6. Structure of the MLP neural network

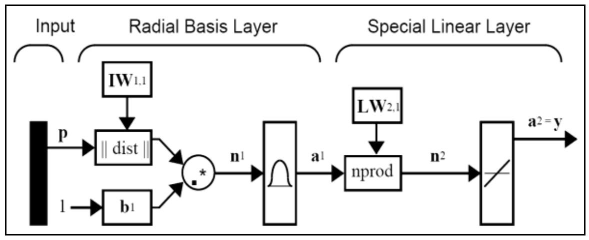

Fig. 7. Structure of the GRNN neural network

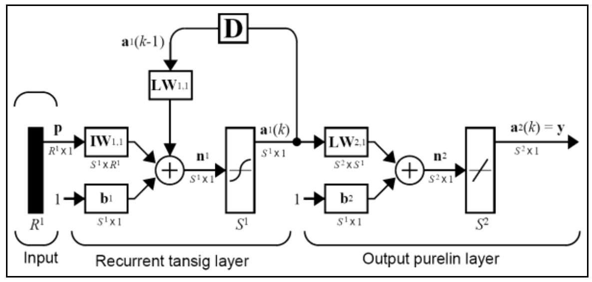

Fig. 8. Structure of the Elman neural network

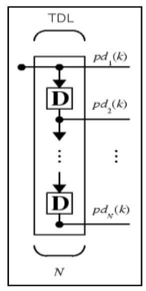

Fig. 9. Structure of the neural networks input (TDL)

4. SIMULATIONS

In this research, performance of different types of neural networks in active cancellation of acoustic noise is evaluated and compared. As it was seen, we use similar structures, equal number of layers and neurons, for designing the neural networks to compare them properly. Moreover, training and test samples are similar. Noise signals from a SPIB are used for simulation procedures. In this section, SPIB database is described at first and then simulation results are presented.

4.1. SPIB Database

SPIB database have been provided by the Rice University [16]. SPIB database consists of acoustic noise from different environments such as engine room, factory environment, aircraft cockpit, car interior noise and etc. In [17] and [18], by using SPIB database, different types of ANC systems and ANC algorithms are investigated. In [19], destroyer operation room noise, and also engine room and F16 cockpit noise are canceled by using feedback ANC system. For this reason, MLP neural network is designed and the noise attenuation of 20 dB is achieved.

4.2. Simulation Results

Various types of acoustic noise are used in this research. For this reason, acoustic noise from a factory environment, F16 cockpit noise, and M109 tank noise are selected from SPIB database. These acoustic noise signals were recorded at a sampling rate of 19.98 kHz with 16 bit resolution. Noise samples are split into two parts, training sets (2000 samples) and testing sets (other samples). After training the networks with each noise, test procedure is done three times. Test samples consist of 5000 samples of noise. In test procedure, performance of the trained networks in noise attenuation is evaluated and compared. Noise attenuation is calculated from,

$$Noise\ Attenuation = 10 \times \log_{10} \frac{Input\ Noise\ Energy}{Remained\ Noise\ Energy} \quad (7)$$

Factory noise is used in first simulation. Noise signal from a factory was recorded near plate-cutting and electrical welding equipment. In table 1, the performance of neural networks in noise attenuation is shown. As it is seen, Elman neural network has better performance than MLP and GRNN networks.

Table 1. Performance of the trained networks in noise attenuation of factory

	The Noise Attenuation (dB)		
	Feed-Forward Networks		Recurrent Network
	MLP	GRNN	Elman
1st test	20.656	19.826	21.386
2nd test	18.98	18.263	19.96
3rd test	21.754	19.345	22.413

Suppose that 2000 samples of factory noise are fed to the trained MLP network. Power spectrum of the factory noise and residual noise are shown in Fig. 10. The dashed line represents the factory noise spectrum and the solid line denotes the residual noise spectrum. From these two spectra, it is concluded that the ANC system achieved good noise reduction from 0-1.5 kHz.
Table 2 shows the performance of trained networks in noise attenuation of F16 cockpit. F16 cockpit noise was recorded at the co-pilot's seat in a two-seat F16, traveling at a speed of 500 knots, and an altitude of 300-600 feet. The proper performance of Elman and MLP networks in comparison with GRNN is derived again.

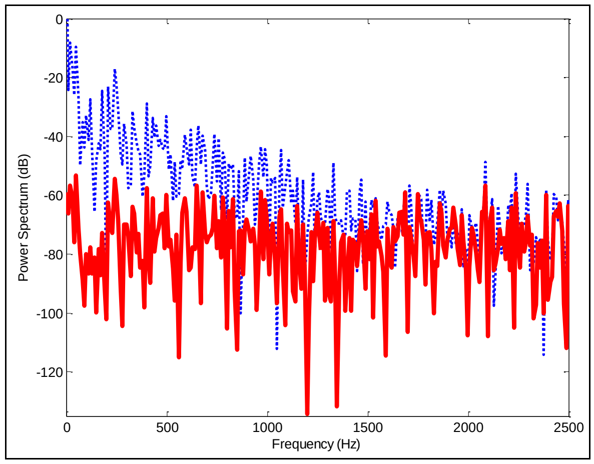

Fig. 10. Factory noise spectrum (dashed line) and residual noise spectrum (solid line)

Table 2. Performance of the trained networks in noise attenuation of F16 cockpit

	The Noise Attenuation (dB)		
	Feed-Forward Networks		Recurrent Network
	MLP	GRNN	Elman
1st test	23.915	19.664	25.242
2nd test	23.615	19.138	24.782
3rd test	23.981	19.652	25.076

Fig. 11 shows 500 samples of F16 cockpit noise (Upper Fig). Anti-noise signal generated with GRNN is shown in the bottom of Fig. 11 (Bottom Fig). It is seen that noise and anti-noise signals are vise versa. The addition of noise and anti-noise signals is called residual noise and is shown in the middle of Fig. 11 (Middle Fig).

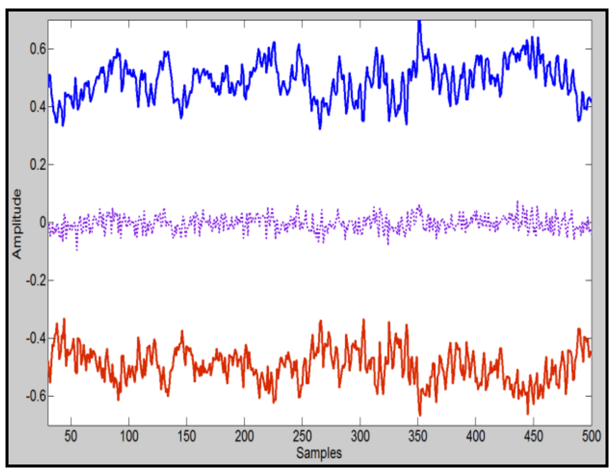

Fig. 11. Upper Fig.: F16 Noise signal, Bottom Fig.: Anti-Noise signal, Middle Fig.: Residual Noise

Third simulation is done with M109 tank noise. The M109 tank was moving at a speed of 30 km/h. The performance of the networks in noise attenuation is shown in table 3.

Table 3. Performance of the trained networks in noise attenuation of M109 tank

	The Noise Attenuation (dB)		
	Feed-Forward Networks		Recurrent Network
	MLP	GRNN	Elman
1st test	27.752	23.824	28.249
2nd test	25.572	22.271	26.161
3rd test	26.561	22.731	27.106

Fig. 12 shows power spectrum of M109 tank noise (2000 samples) and residual noise spectrum obtained by Elman neural network. From these spectra, it is seen that the designed ANC system achieved good noise reduction from 0-2 kHz.

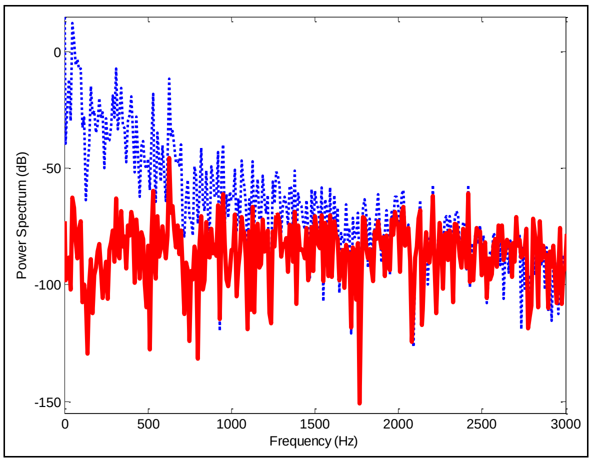

Fig. 12. M109 tank noise spectrum (dashed line) and residual noise spectrum (solid line)

From tables 1-3, it is concluded that Elman and MLP neural networks can cancel the noise more efficient than GRNN. From Figs. 10 and 12, it is demonstrated that designed ANC system achieved good noise reduction in low frequencies.

By comparing the required time for training and testing the networks, it was seen that GRNN needs more time for producing anti-noise signal than MLP and Elman networks but it requires less training time. MLP and Elman networks require similar time in network testing but Elman network needs more time for training. Moreover, appropriate processor should be selected for implementing ANC system because of the complex structure of Elman network.

5. CONCLUSIONS

In this paper, comparison of different types of neural networks in active cancellation of acoustic noise was performed. MLP, Elman and GRNN neural networks with similar architectures were investigated and compared in simulation procedures. Acoustic noise signals from SPIB database were used for training and testing the networks. The results of simulations demonstrated that MLP, Elman and GRNN neural networks have appropriate performance in noise attenuation. Power spectrum of the main noise and residual noise showed that neural networks achieved good noise reduction in low frequencies.

It was concluded that Elman and MLP networks can cancel the noise more efficiently than GRNN. Comparing the required time for training and testing the networks demonstrated that GRNN needs less time for training than MLP and Elman networks but it requires more time in testing process. Moreover, MLP requires less time than Elman neural network in training process.

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