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Application of Neural Networks in Active Noise Reduction Systems

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Active noise reduction systems based on a control unit in the form of a finite impulse response filter assume the linearity of every single component. Neural networks, which have so far been seldom used in this field, are a kind of a filter with the ability to project nonlinear characteristics of an active noise reduction system. This paper presents some simulation research studies of active noise reduction systems based on neural networks. Also presented are results of the operation of systems with different levels of complexity as well as the influence of different parameters of a neural network and of the system itself on those results.

noise active methods control neural network

1. INTRODUCTION

Active noise reduction is based on the phenomenon of mutual compensation of acoustic waves leading to a decrease in the sound pressure level at a given point in space (Engel & Kowal, 1995; Engel, Makarewicz, Morzyński, & Zawieska, 2001; Hansen & Snyder, 1997). Figure 1 is a general diagram of an active noise reduction system.

A compensating acoustic wave is created by means of an additional sound source. In order to reduce noise at the point in space we are interested in (the

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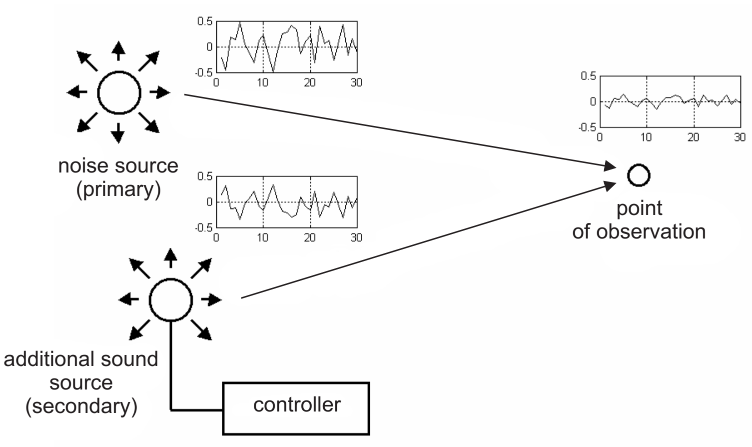

Figure 1. A general diagram of an active noise reduction system.

point of observation), an acoustic compensation wave has to have at this point the same amplitude as the acoustic noise wave and an opposite phase. The secondary sound source should be controlled in such a way that it fulfills the aforementioned condition with the highest achievable accuracy. A controller that drives the secondary source should analyze a noise signal and generate an adequate compensating signal, taking into account transfer functions of the elements of the electroacoustic path, including phase shift results from different distances between sources and the point of observation.

Because of the requirements that a control unit must fulfill, most often it has the form of some kind of a digital filter. Because in general not all transfer functions are known and, in addition, these functions can vary in time, the control filter is most often an adaptive filter (Engel et al., 2001; Makarewicz, Matuszewski, Morzyński, & Zawieska, 2000). That is why it can change its parameters by itself in such a way that it increases the efficiency of an active noise reduction system.

The most frequently used filter type is a finite impulse response (FIR) filter. Adaptive algorithms used with this filter are not computationally very complex, but control based on this filter does not take into account nonlinear phenomena. Artificial neural networks are free of this disadvantage. Until recently, for various reasons (especially the considerable complexity of calculations and a relatively long time of adaptation of a neural network) their application in active noise reduction systems was rather limited.

In the next part of this paper fundamental problems concerning neural networks are briefly discussed. Some results of a simulation of active noise reduction systems based on neural networks are also presented. All simulations were made in a Matlab environment.

2. NEURAL NETWORKS IN ACTIVE NOISE REDUCTION SYSTEMS

Artificial neural networks originated as a kind of a model of a biological neural system (Nałęcz, Duch, Korbicz, Rutkowski, & Tadeusiewicz, 2000). The basic element of a neural network is a neuron, which is presented in Figure 2. Like its biological equivalent it has *N* inputs and one output. In a neural network each neuron output is connected with inputs of other neurons depending on the network structure (Engel & Nizioł, 1995; Engel et al., 2001; Sarle, 2002).

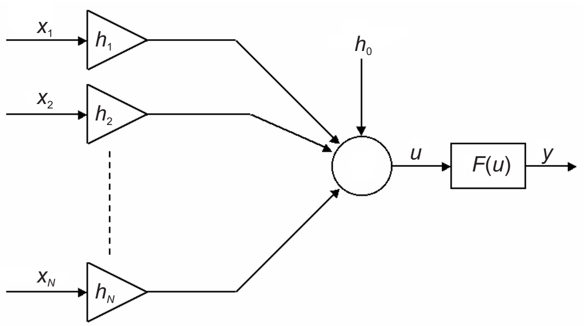

Figure 2. A neuron.

Output signal *y* of a neuron is a function of the sum of weighted input signals *x* in accordance with the following formula:

$$y = F(u) = F(h_0 + \sum_{i=1}^{N} x_i h_i)\,, \tag{1}$$

where h_0 is the nodal bias and h_i are weights of input signals. In the following part of the paper it is assumed that in the analyzed networks $h_0 = 0$. The function $F(u)$ is called an activation function. Most often a unit step function, a linear function, a logistic curve, or a hyperbolic tangent are used as $F(u)$. In the described active noise reduction (ANR) system a hyperbolic tangent is used as an activation function. It is given by

$$F(\beta u) = tgh(\beta u) = \frac{1 - e^{-2\beta u}}{1 + e^{-2\beta u}}\,. \tag{2}$$

Figure 3 shows a plot of the $tgh(\beta u)$ function for different values of β.

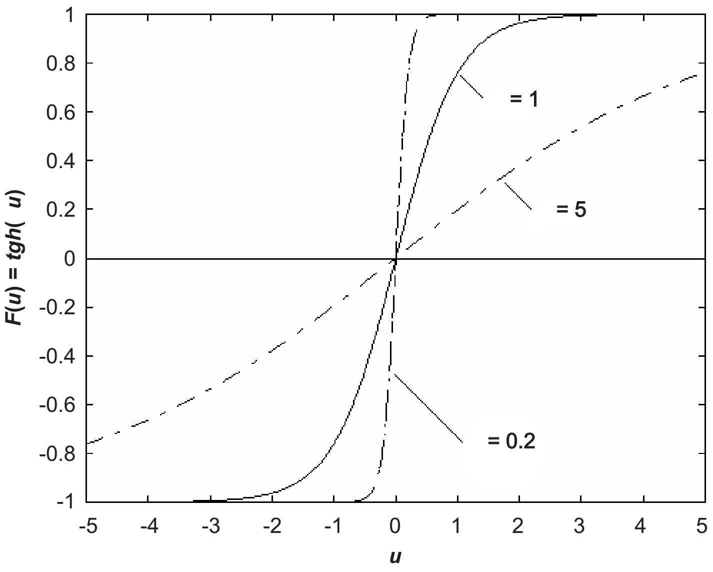

Figure 3. The activation function *tgh*(β*u*) for different values of β.

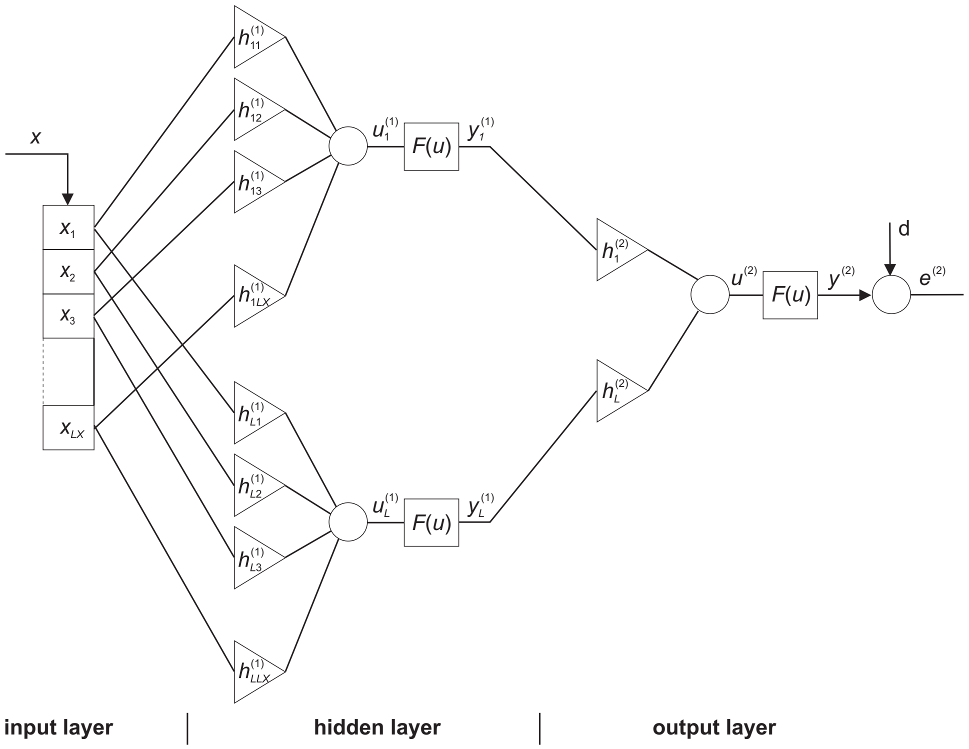

Figure 4. A multilayer feedforward neural network.

As mentioned before there are many types of neural networks, which differ in the neuron connection. Figure 4 presents an example of a multilayer feedforward neural network on which an ANR system is based.

This network consists of the input layer *IL*, one or more hidden layers *HL*, and the output layer *OL*. The input layer of a neural network is a tapped delay line in which one tap can be treated as an elementary neuron. Each neuron of a given layer is connected with all neurons of the preceding layer. Signals in a network propagate only in the direction from input to output (there is no feedback). The operation of a network with one hidden layer and one neuron in the output layer presented in Figure 4 is described by Equations 3 and 4:

$$y_k^{(1)}(n) = F\left(\sum_{i=1}^{LX} x_i(n) h_{ki}^{(1)}(n)\right), \tag{3}$$

$$y^{(2)}(n) = F\left(\sum_{i=1}^{L} y_i^{(1)}(n) h_i^{(2)}(n)\right), \tag{4}$$

where LX is the number of taps in the input layer, L is the number of neurons in the hidden layer, and the superscript indicates the number of the neuron layer counting from the first hidden layer. The output signal of a network $y^{(2)}$ is a compensating signal of an active noise reduction system. The aim of a learning process (adaptation) of a network is the minimization of a squared error $(e^{(2)})^2$, where

$$e^{(2)}(n) = d(n) + y^{(2)}(n). \tag{5}$$

One of the most popular learning algorithms is the back propagation algorithm (Hansen & Snyder, 1997; Nałęcz et al., 2000; Rutkowski, 1994). According to this algorithm, for a network presented in Figure 4, the weights of a neuron in the output layer will be updated according to Equation 6:

$$\mathbf{h}^{(2)}(n+1) = \mathbf{h}^{(2)}(n) - \mu \mathbf{y}^{(1)} e^{(2)} F'(u^{(2)}) \tag{6}$$

and the weights of the neurons in the hidden layer according to Equation 7:

$$\mathbf{h}_k^{(1)}(n+1) = \mathbf{h}_k^{(1)}(n) - \mu \mathbf{x}(n) e_k^{(1)}(n) F'(u_k^{(1)}), \tag{7}$$

where

$$\mathbf{e}^{(1)}(n) = e^{(2)}(n)F'(u^{(2)}(n))\mathbf{h}^{(2)}(n) \tag{8}$$

and μ is the learning factor, as a rule selected experimentally from the interval (0, 1).

Assuming that $tgh(\beta u)$ is the activation function

$$F'(u) = \beta(1 - F^2(u)) = \beta(1 - (y^{(2)})^2), \tag{9}$$

which allows us to significantly simplify calculations.

3. SIMULATIONS

Figure 5 presents a block diagram of the considered ANR system.

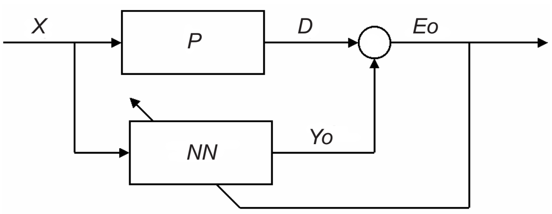

Figure 5. A block diagram of an active noise reduction system.

The noise signal *X* (the reference signal) after propagating through the acoustic path *P* reaches the point of observation as a signal *D*. On the basis of the knowledge of the signal *X* the neural network *NN* generates the compensating signal *Yo* on its output. The error signal *Eo* is the sum of the noise signal *D* and the compensating signal *Yo*. In the analyzed system it is assumed that a secondary source and an error signal detector are located at the observation point. The neural network *NN* is similar to the network presented in Figure 4. It has one hidden layer and an output layer with one neuron. The learning process of the network takes place in accordance with Equations 5–9. In simulations two types of reference signals were used: a pure sinusoid of frequency 100 Hz and pseudorandom noise.

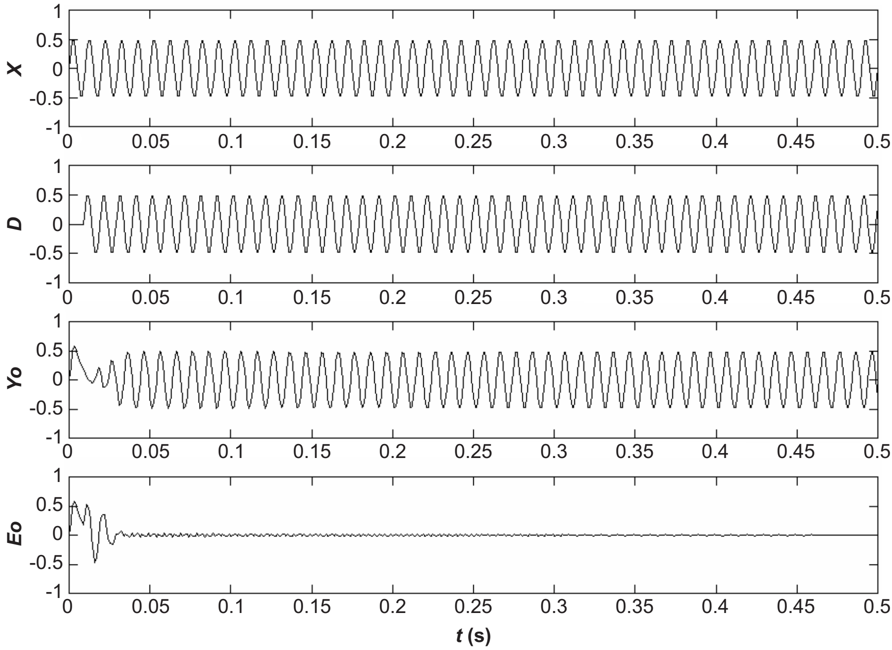

Figure 6. Signals in a simulated active noise reduction system for sinusoidal noise.

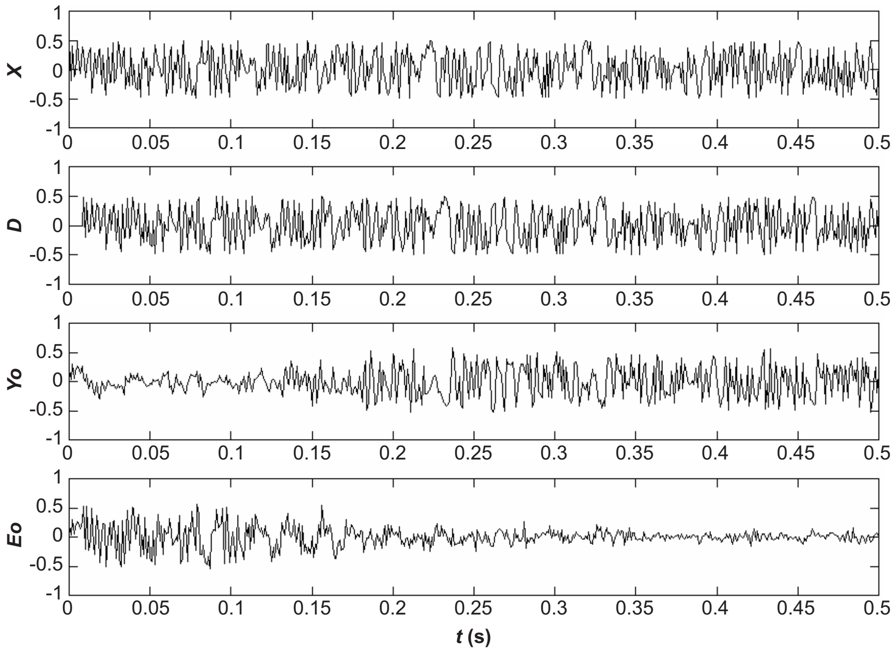

Figure 7. Signals in a simulated active noise reduction system for pseudorandom noise.

Figure 6 presents the performance of an active noise reduction system for sinusoidal noise, and Figure 7 for pseudorandom noise. During calculations it was assumed that $\mu = 0.5$, $L = 2$, $LX = 20$, $Tp = 1$ kHz, and the delay of the channel P was 0.01 s. From the figures it appears that the active noise reduction system based on a neural network is capable of effectively reducing simulated noise. Unfortunately the adaptation time is relatively long, even for a network of a simple structure.

The next experiment concerned the behavior of a neural network in the case of the nonlinear acoustic channel P. In the simulation the reference signal X was a single tone. After transmitting through the acoustic channel P two additional tones appeared in this signal. These tones were the 3rd and the 5th harmonics of this tone (Figure 8).

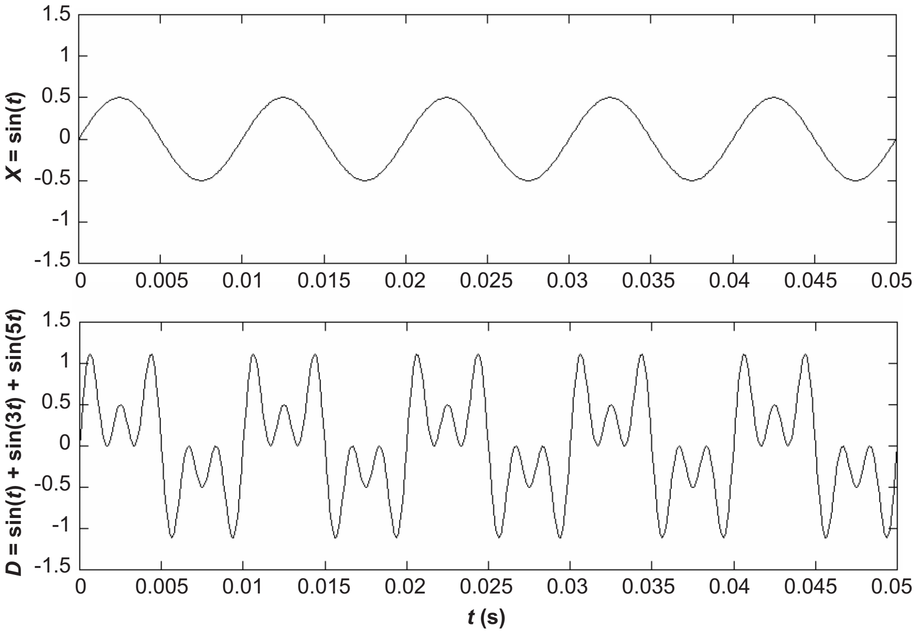

Figure 8. The reference signal before (*X*) and after (*D*) passing through the nonlinear acoustic path.

Figures 9 and 10 present error signals of active noise reduction systems with the use of a FIR filter and a neural network for different types of the acoustic path P. During calculations it was assumed that $\mu = 0.5$, $L = 2$, $LX = 20$, $Tp = 1$ kHz; the delay of the channel P was 0.01 s and the length of the FIR filter was 20.

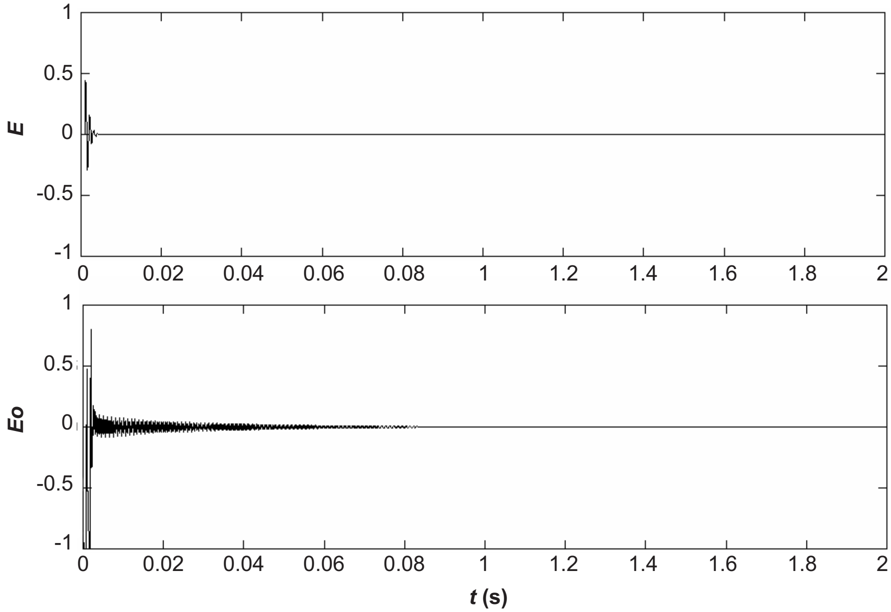

Figure 9. **Error signals of active noise reduction systems based on the finite impulse response (FIR) filter (*E*) and a neural network (*Eo*) for the linear acoustic path *P*.**

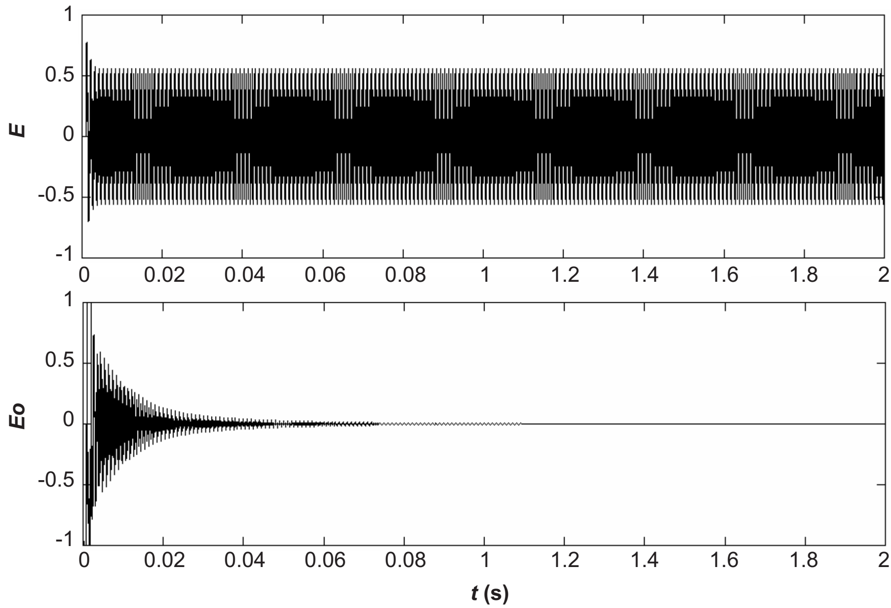

Figure 10. **Error signals of active noise reduction systems based on the finite impulse response (FIR) filter (*E*) and a neural network (*Eo*) for the nonlinear acoustic path *P*.**

From the aforementioned figures it can be seen that in the case of the linear acoustic path *P* the FIR filter has better convergence than a neural network. At the same time this filter is not capable of reducing noise where the acoustic path *P* is nonlinear.

Figure 11 presents the results of the performance of an active noise reduction system for the linear acoustic path *P* and different numbers of neurons in the hidden layer.

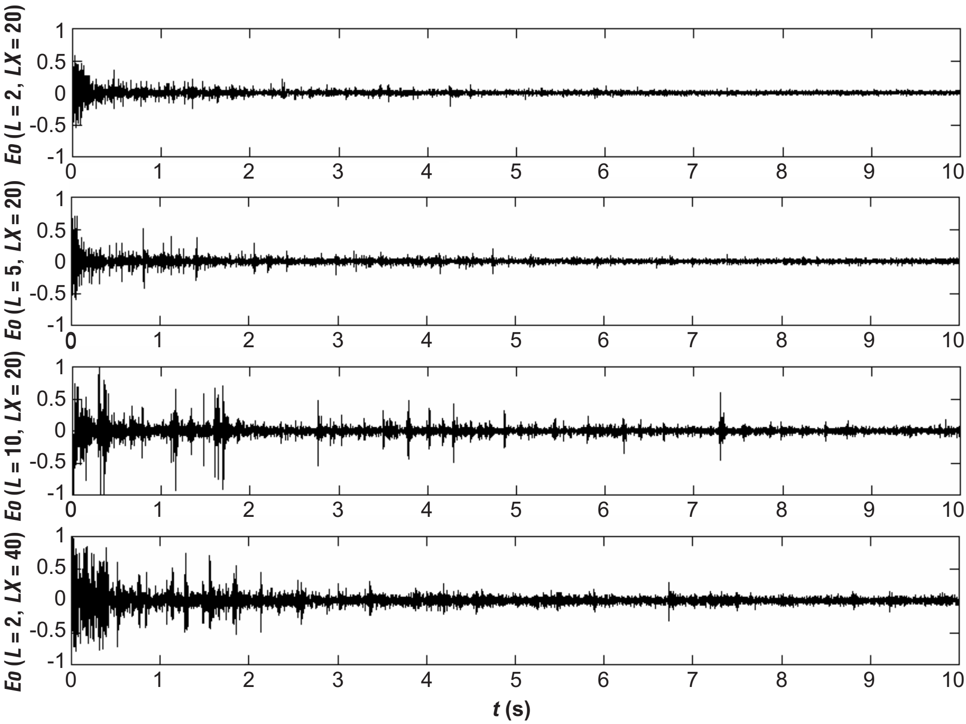

Figure 11. The performance of an active noise reduction system for the linear acoustic path *P* and different numbers of neurons in the hidden layer.

During the calculations it was assumed that $\mu = 0.5$, $Tp = 1$ kHz, and the delay of the channel *P* was 0.01 s. Noise was simulated as a pseudorandom signal. From the simulation it appears that increasing the number of neurons in the hidden layer has an unfavorable influence on the performance of the system. Due to a large number of network coefficients the adaptation time is long.

The situation is opposite when it is assumed that the acoustic path *P* is nonlinear (Figure 12). During calculations it was assumed that $\mu = 0.5$, $LX = 20$, $Tp = 1$ kHz; the delay of the channel *P* was 0.01 s and the length of the FIR filter was 20. Signals *X* and *D* were the same as in Figure 8.

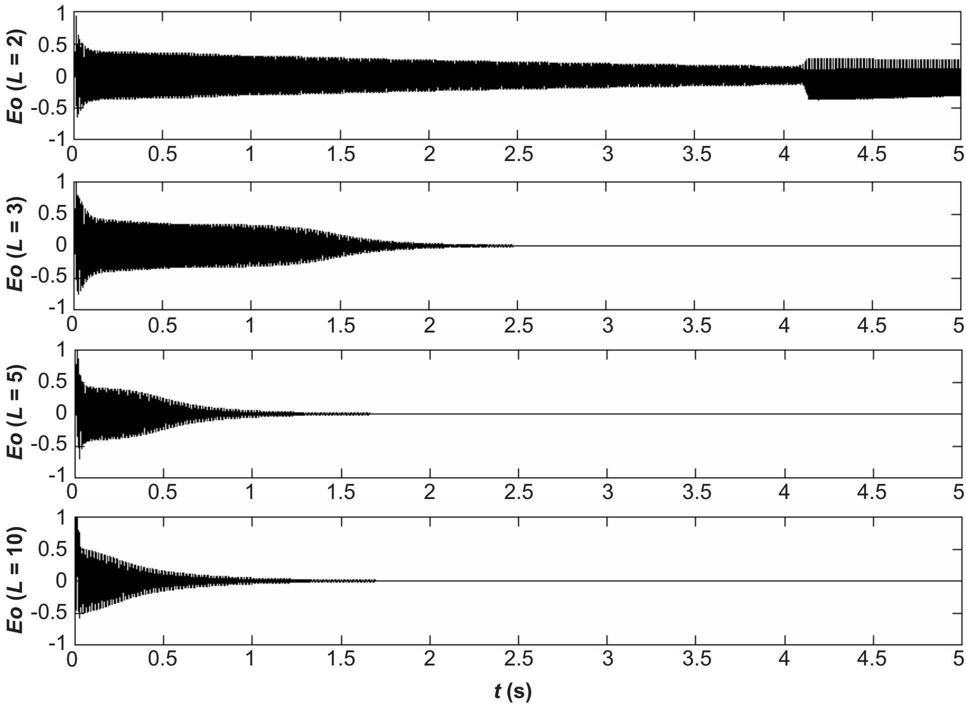

Figure 12. The performance of an active noise reduction system for the nonlinear acoustic path *P* and different numbers of neurons in the hidden layer.

The results of the simulation indicate that for good performance of the active noise reduction system the number of neurons in the hidden layer should be at least equal to the number of harmonic tones in the compensated signal *D*. A further increase in the number of neurons slightly influences the effectiveness of the system, and at the same time has a significant influence on the complexity of calculations.

The last experiment described in this paper concerns the application of a neural network in a two-channel system (Figure 13). For simplicity it was assumed that compensating signals do not influence each other and that two acoustic channels have the same linear acoustic path *P*. Now, the neural network has two neurons in the output layer. Equations 4, 5, 6, and 8 in a two-channel system take the form of Equations 10, 11, 12, and 13 accordingly.

$$y_m^{(2)}(n) = F\left(\sum_{i=1}^{L} y_i^{(2)}(n) h_{mi}^{(2)}(n)\right) \tag{10}$$

$$e_m^{(2)}(n) = d_m(n) + y_m^{(2)}(n) \tag{11}$$

$$\mathbf{h}_m^{(2)}(n+1) = \mathbf{h}_m^{(2)}(n) - \mu \mathbf{y}^{(1)} e_m^{(2)} F'(u_m^{(2)}) \tag{12}$$

$$e_k^{(1)}(n) = e_1^{(2)}(n) F'(u_1^{(2)}(n)) h_{1k}^{(2)}(n) + e_2^{(2)}(n) F'(u_2^{(2)}(n)) h_{2k}^{(2)}(n) \tag{13}$$

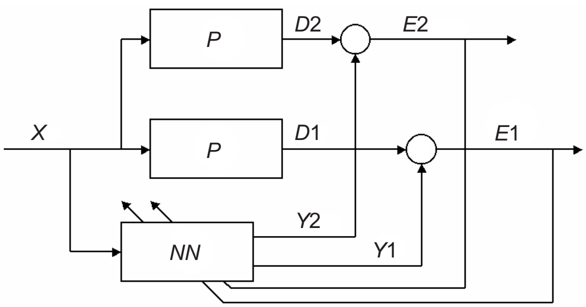

Figure 13. A block diagram of a two-channel active noise reduction system.

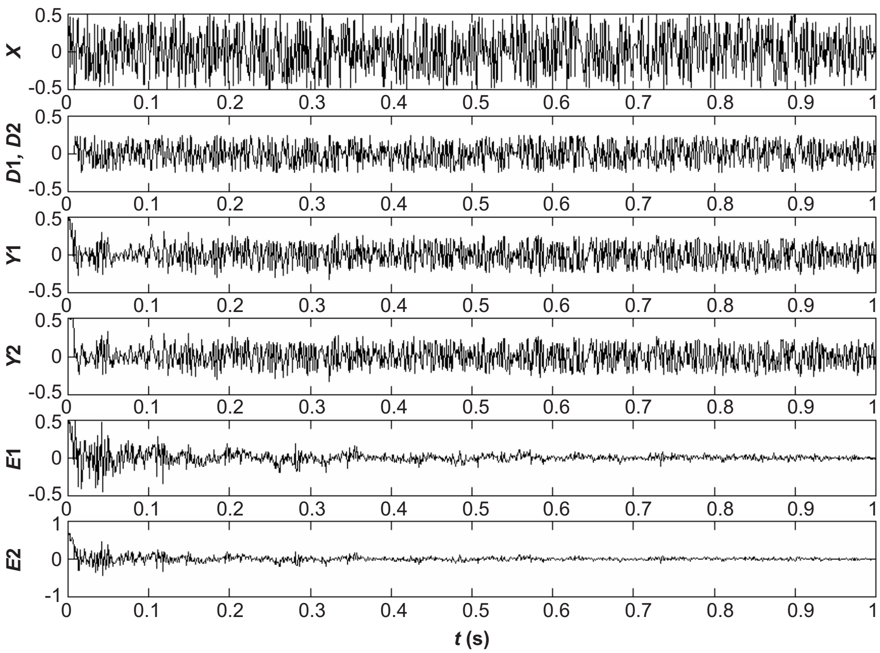

Figure 14. The performance of a two-channel active noise reduction system.

Figure 14 presents simulated results of performance of such a system. During calculations it was assumed that $\mu = 0.5$, $L = 5$, $LX = 20$, $Tp = 1$ kHz, and the delay of the channel P was 0.01 s.

4. CONCLUSIONS

The main disadvantage of applying artificial neural networks in active noise control systems is the complexity of calculations and the long adaptation of the parameters of neural networks. This restricts practical application of such adaptive systems to a stationary or almost stationary noise source. This disadvantage is compensated by the ability of neural network-based ANR systems to deal with nonlinear phenomena encountered in almost all practical applications. Increasing the processing power of digital signal processors and general purpose processors leads to the conclusion that it will soon be possible to disregard the problem of calculation complexity of neural networks in ANR systems.

The simulation experiments that were carried out confirmed usefulness of neural networks in active noise reduction systems, particularly in nonlinear systems and multichannel systems. The reduction of low frequency noise emitted by high power electric transformers is a good example. In the spectrum of this noise odd harmonics of the fundamental frequency of power supply can be found. Moreover to reduce noise emitted by such transformers multichannel active noise reduction systems are recommended.

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