ACTIVE NOISE CONTROL SYSTEM BASED ON NEURAL NETWORK

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INTRODUCTION

Artificial neural networks are a well-known instrument for signal processing but they are seldom used in active noise control (ANC) systems. In comparison to transversal FIR filters neural networks are slower and require more processing power. However, in some cases neural networks can be very useful. A feedforward neural network is a non-linear generalization of a FIR filter and can be used in systems in which non-linear effects play a significant role. A good example may be a system for active reduction of a transformer noise, where a sinusoidal reference signal (from a power network) is used to derive a signal to control a disturbance containing several harmonics of this signal. In these cases a linear adaptive filter can not assure good performance of the system.
Most neural network-based systems for real time signal processing use specialized DSP processors. At present this type of system can be made using an ordinary PC computer. In the Central Institute for Labour Protection, a PC-based low-cost control unit for signal processing in ANC systems was made. Different structures of filters with different types of learning algorithms were implemented in this unit The main aim of the present study was to verify if this control unit is suitable for a neural network-based ANC system. Before the implementation of a neural network, some simulations of the neural network based ANC system were made for better understanding of the behavior of the system. After the implementation, some preliminary measurements of the neural network-based system for active noise reduction in the acoustic duct were made. Results of measurements, simulations and the construction of the control unit are described in this paper. Experiments confirmed that the use of the low-cost controller in the neural network-based ANC system can give good results.

ANC SYSTEM SIMULATIONS

The neural network. The ANC system described in this paper is based on a multi-layer feedforward network [1, 2 and 3]. The structure of the network is shown in *Fig. 1*. It consists of a trapped delay line for reference signal x in an input layer, one layer of neurons in a hidden layer and one neuron in an output layer. In this case one trap in the input delay line can be treated as an 'elementary neuron' in the input layer. During simulations and measurements the number of traps in the input delay line and the number of neurons in the hidden layer were changed. In the succeeding part of this paper LX denotes the number of traps in the delay line and L denotes the number of neurons in the hidden layer. The nodal bias of neurons is zero and the activation function $F(u)$ is a hyperbolic tangent: $F(u) = tgh(u)$. In the symbols upper index given in brackets denotes the layer number starting from the first hidden layer. Lower index denotes the neuron number in given layer and the coefficient number in given neuron. The output signal of the network is denoted by $y^{(2)}$, where d is the disturbance signal and $e^{(2)}$ is the error signal of the system.

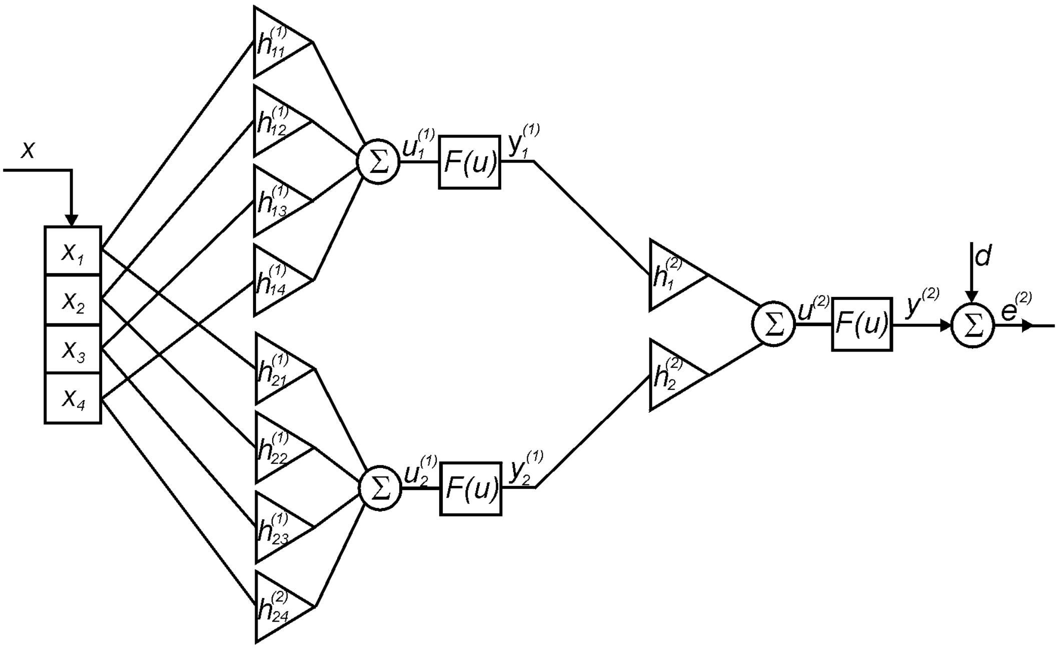

Fig. 1. An example of a multi-layer feedforward neural network.

For the adaptation of a neural network coefficient the standard back propagation algorithm [1, 2, 3] was used. For a given network it takes the following form:

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

$$\mathbf{h}_k^{(1)}(n+1) = \mathbf{h}_k^{(1)}(n) + \mu \mathbf{x}(n) e_k^{(1)}(n)(1-(y_k^{(1)}(n))^2) \tag{2}$$

$$\mathbf{e}^{(1)}(n) = e^{(2)}(n)(1-(y^{(2)}(n))^2)\mathbf{h}^{(2)}(n) \tag{3}$$

where $e^{(1)}$ is the error "back propagated" to the hidden layer and μ. is the learning factor.

Simulations. Simulations were made to define the influence of the system and the network parameters on its behavior and efficiency. They were very helpful for the evaluation of the real system.

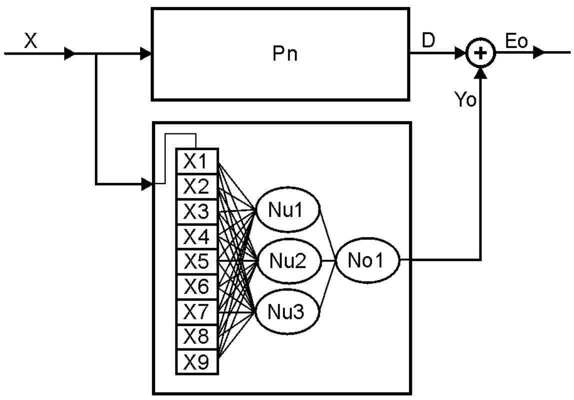

Fig. 2. A block diagram of the simulated system.

An elementary block diagram of the simulated system is shown in *Fig. 2*. It is a simplified model of the neural network-based system for active noise reduction in the acoustic duct. X is the reference signal (noise) and Pn is the transfer function of the acoustic path. The disturbance signal D is the reference signal transferred through the acoustic path. The acoustic path delays the reference signal and in some simulations it creates non-linear disturbances. The structure of the control network shown in *Fig. 2* is one of many possible solutions. During simulations a number of neurons in input and hidden layers were changed. Three different reference signals were used: sinusoidal, sum of sinusoidal signal and its first harmonic and a sum of sinusoidal signal and its first and third harmonics. The coefficients of the network were initiated by random generator. The influence of the number of neurons, the reference signal type, the learning factor μ and the delay of the acoustic path on the system behavior were investigated. No error path transfer function was considered in simulations because it would be too complex for the real time system implementation.

Simulations were made using Matlab environment but without built-in toolboxes. Simulation procedures were based on the same code as the software implemented in the control unit. This allowed to verify algorithms and define the influence of errors on the system behavior.

In the simulations the reference signal was a sum of sinusoidal signal and its first harmonic; the results are shown in *Fig. 3* and *Fig. 4*. In both cases the learning factor was 0.45 but systems had different numbers of neurons. As seen in *Fig. 4,* a small number of neurons in the input layer leads to poor efficiency of the system.

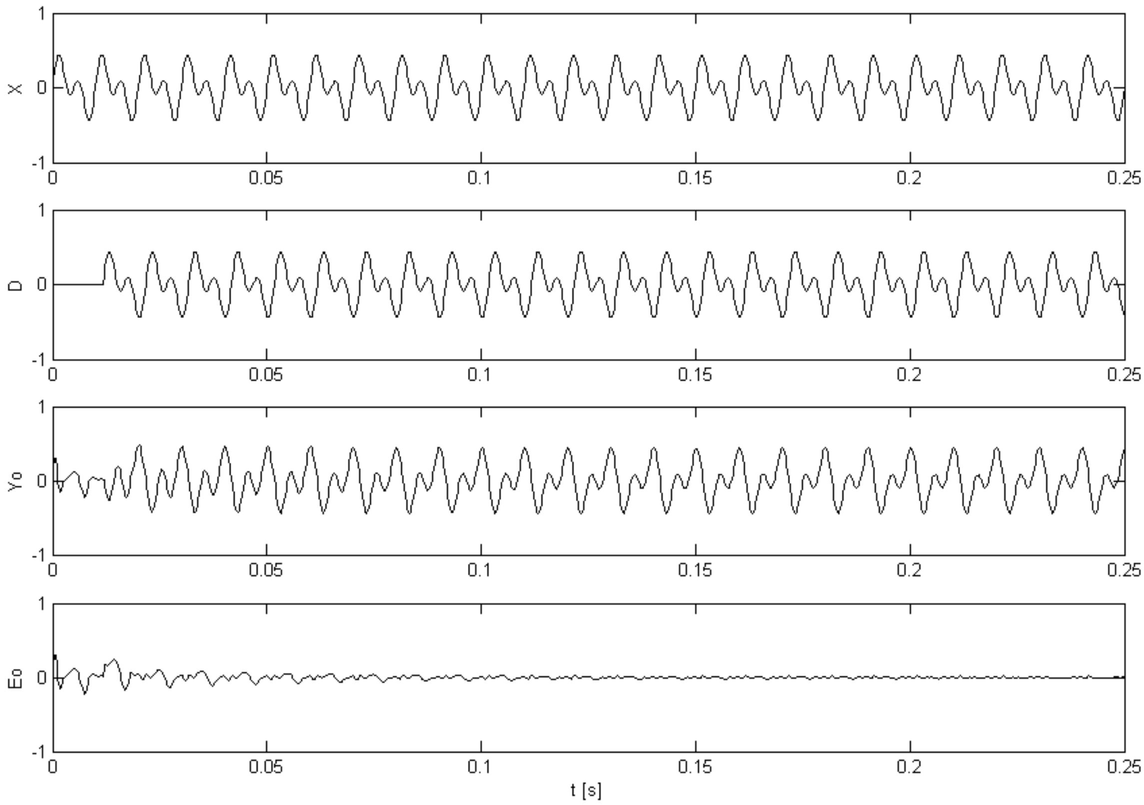

Fig. 3. Signals in the simulated system based on the neural network with 9 neurons in the input layer and 2 neurons in the hidden layer.

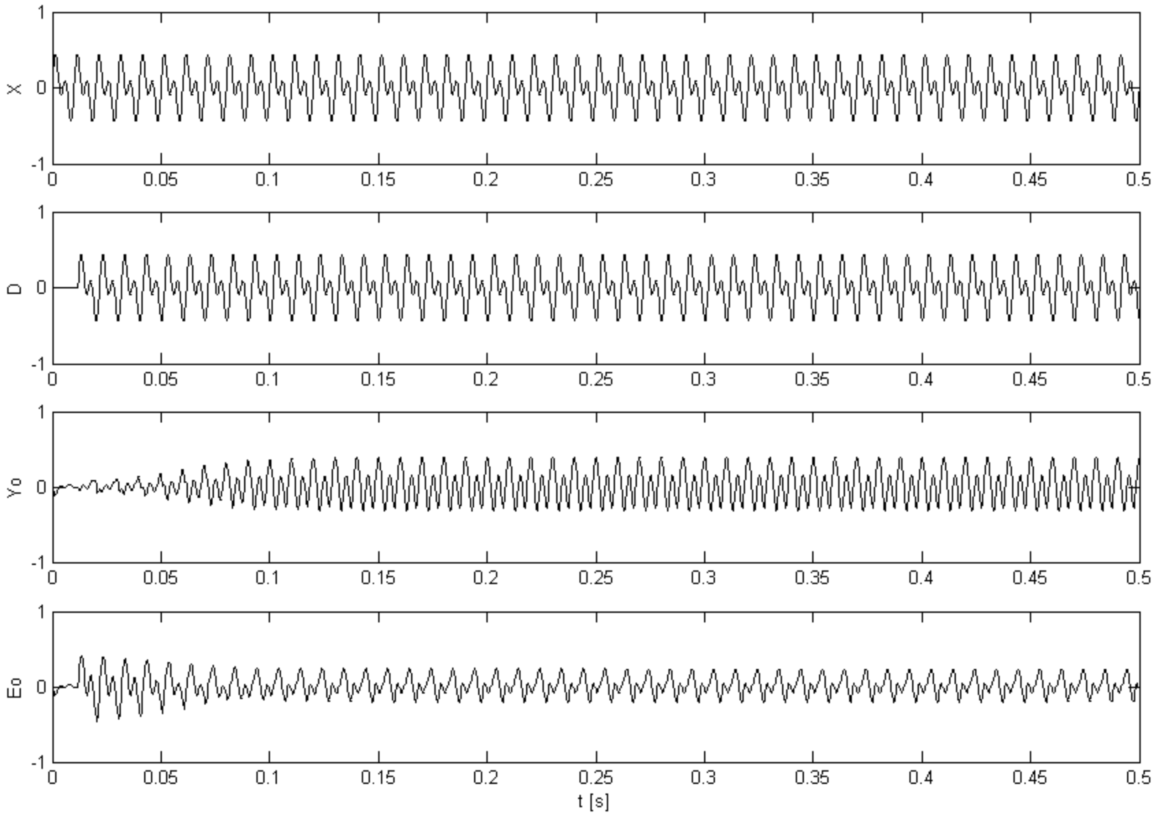

Fig. 4. Signals in the simulated system based on the neural network with 3 neurons in the input layer and 2 neurons in the hidden layer.

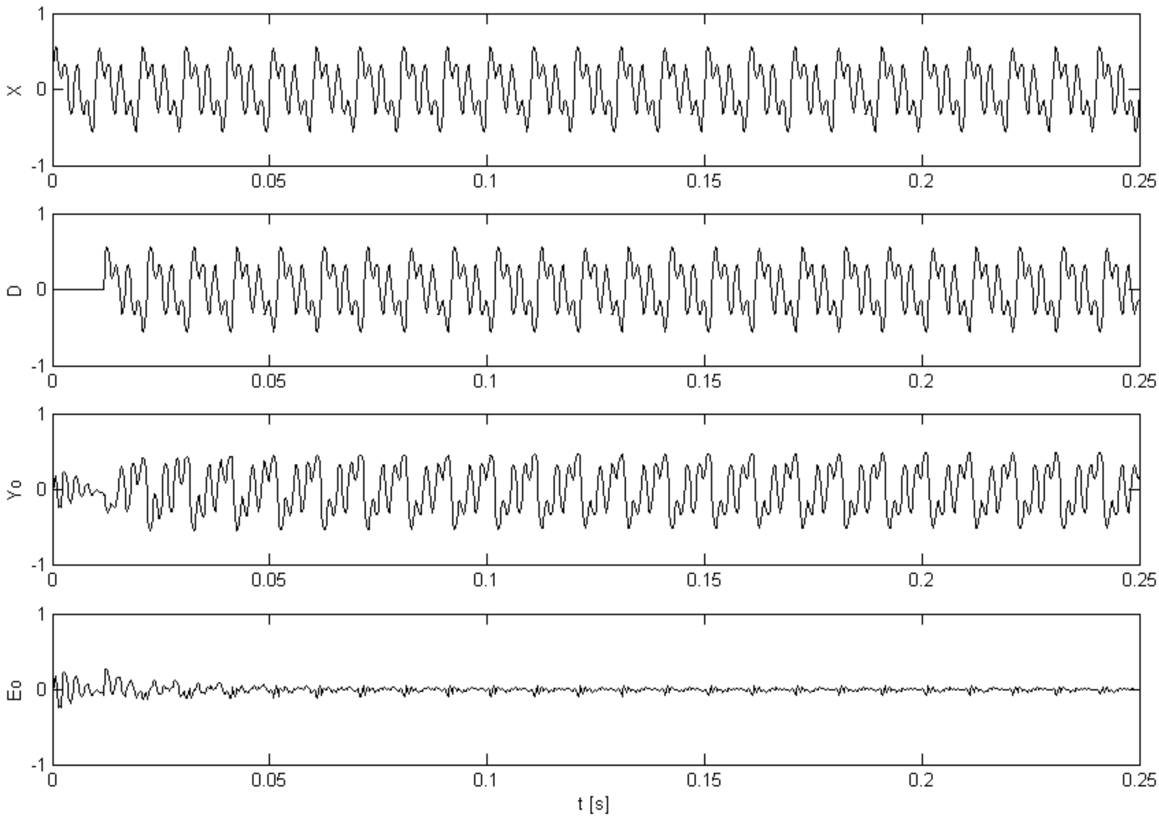

Fig. 5. Signals in the simulated system based on the neural network with 9 neurons in the input layer and 3 neurons in the hidden layer.

Results of simulation in which the reference signal was the sum of the sinusoidal signal and its first and third harmonics are shown in *Fig. 5*. The neural network had 9 neurons in the input layer and 3 neurons in the hidden layer. The learning coefficient was 0.45. This kind of simulated network was able to completely reduce the disturbance.

During simulation the ability of reducing noise in non linear systems was also tested. Non-linear acoustic transfer path was simulated by adding to the reference signal its harmonics (third and fifth). It gives the disturbance signal as shown in *Fig. 6.*

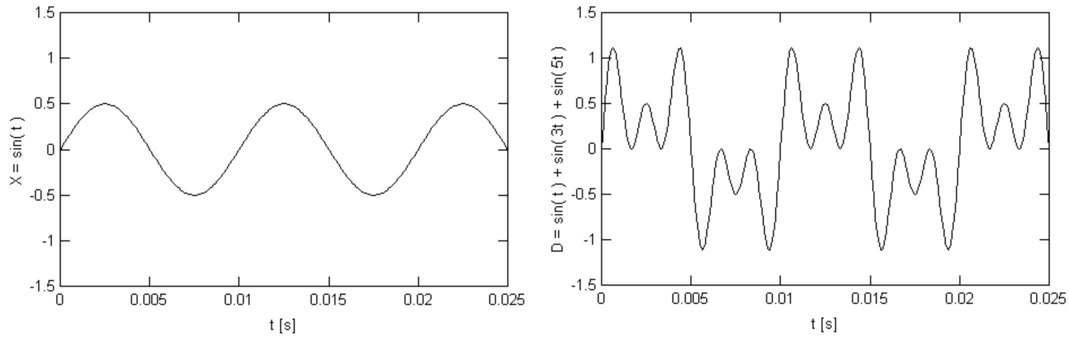

Fig. 6. The reference signal (left) and the disturbance on the output of the non-linear acoustic path (right).

The efficiency of the simulated non-linear system for different number of neurons in the hidden layer is shown in *Fig. 7*. In all cases the number of neurons in the input layer was the same:

LX = 20.

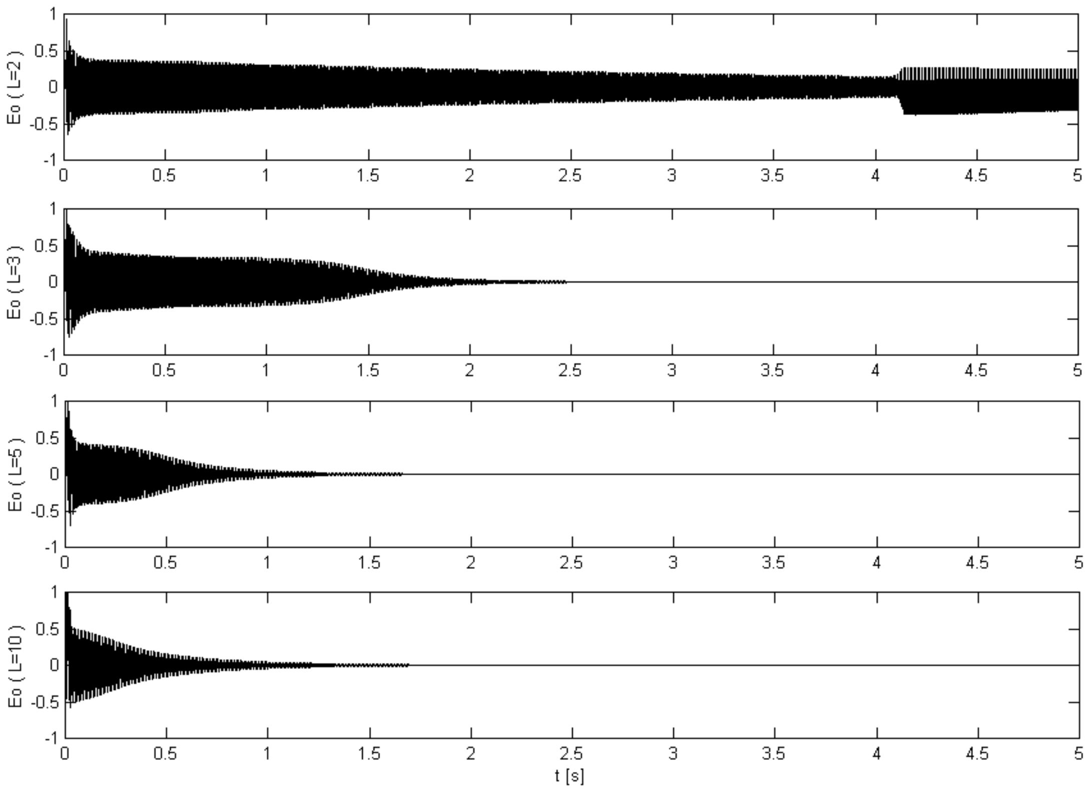

Fig. 7. The error signal for different number of neurons in the hidden layer of the neural network in the simulated ANC system.

The number of neurons in the hidden layer should be at least equal to the number of harmonics in the disturbance signal.

THE CONTROL UNIT

The control unit was based on components of an ordinary PC computer mounted in a standard industrial 19-inch case as shown in *Fig. 8*. In this way the controller is better adapted for industrial conditions.

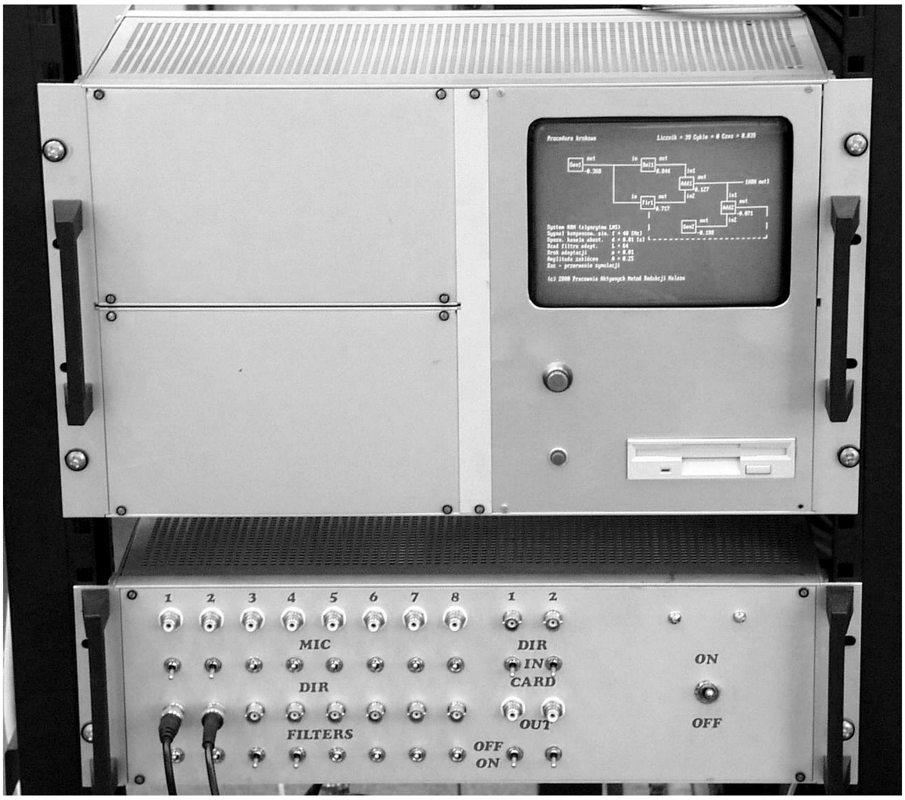

Fig. 8.The control unit (above) with the conditioning (input/output) unit (below).

The heart of this unit is a general purpose processor made by Intel, working at a frequency 500MHz. For analog data acquisition and signal generation, a low-cost analog I/O board is used. The board type CIO-DAS08/JR-AO was manufactured by ComputerBoards. It has eight analog input channels with 20kHz maximum sampling rate and two analog output channels. Both types of analog channels have a 12-bit resolution and voltage range ± 5V. For this reason the control unit may be used in ANC systems having a maximum of two control sources and eight detectors. Of course the I/O board can be easily replaced by another board having better parameters. The control unit also has a built-in 7" monochrome VGA monitor. This monitor is used in real conditions for setting up and maintaining the controller. During the experiments another external monitor is used to increase working comfort of programmer.

An integral part of the control system is a conditioning unit shown in *Fig. 8*. It is used for limiting, filtering, amplifying and restoring input and output signals. The unit has eight direct inputs and eight polarized inputs for electret microphones. The type of input signal in every channel is set with switches.

Both units described above communicate by cable with 37-pin connectors.

Software is a very important part of the control unit. It was written in C++ language using object programming with necessary insertions in assembler. The software components can be defined as class library as shown in *Fig. 9*. Classes are associated using inheritance mechanism. The base class for the whole library is the class named TAncBaseObject. Different types of instruments classes (e.g. generators, amplifier, transversal filters, oscilloscope) and algorithms classes were defined in the library. Software can be used for real time signal processing and for simulations. Class TAncRealProc can be used for real signal processing while class TAncStepProc - for simulations. Classes directly related to the neural network are thicken on the library structure.

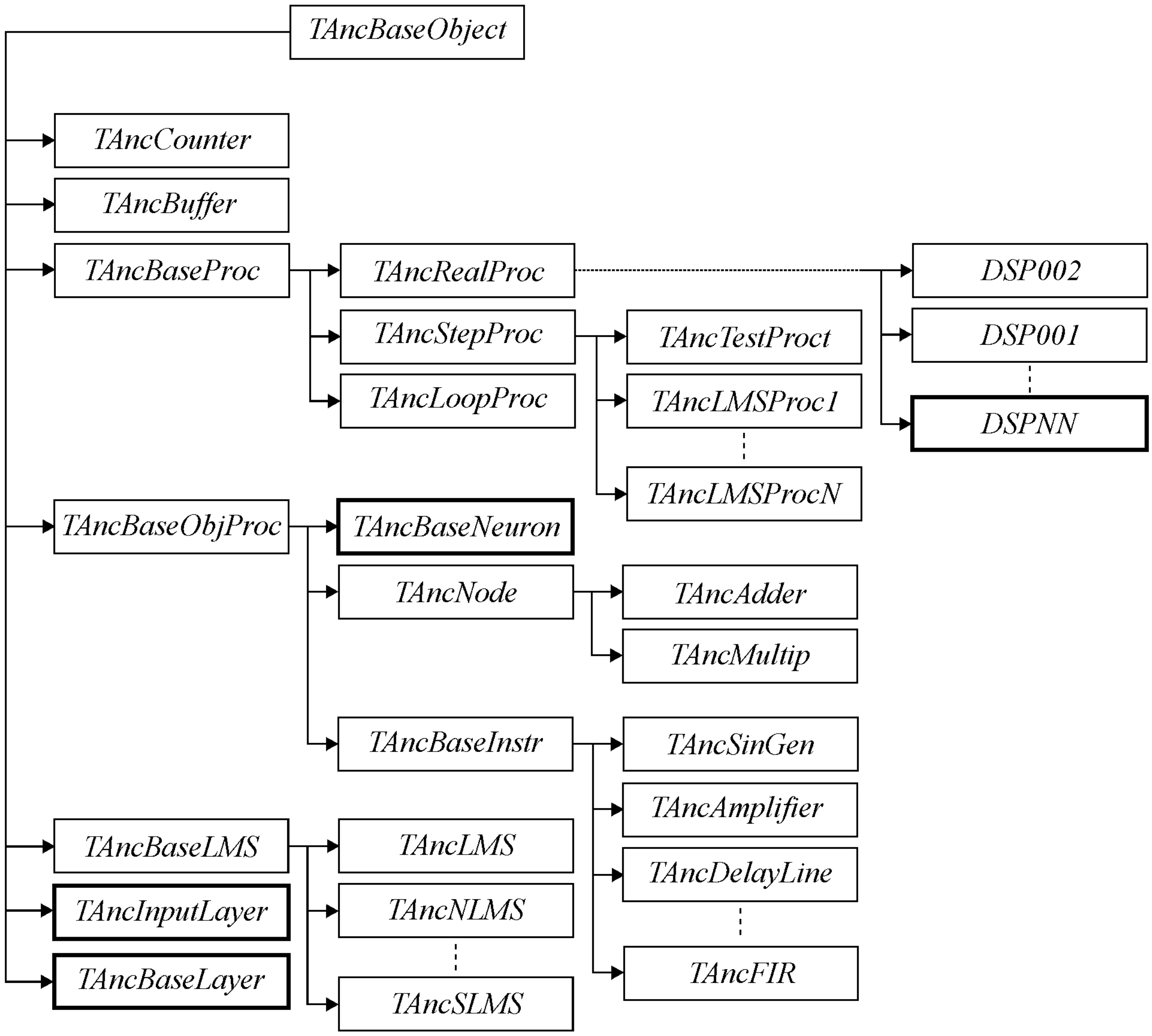

Fig. 9. The structure of the class library of the control unit software.

The operating system of the controller is DOS. Small program codes, small memory requirements and direct control of all system components are an advantage of this operating system. Both the system and software can be run from a floppy disc.

MEASUREMENTS

Measurements of the efficiency of the neural network-based ANC system were made on a laboratory stand [4] presented in *Fig. 10*.

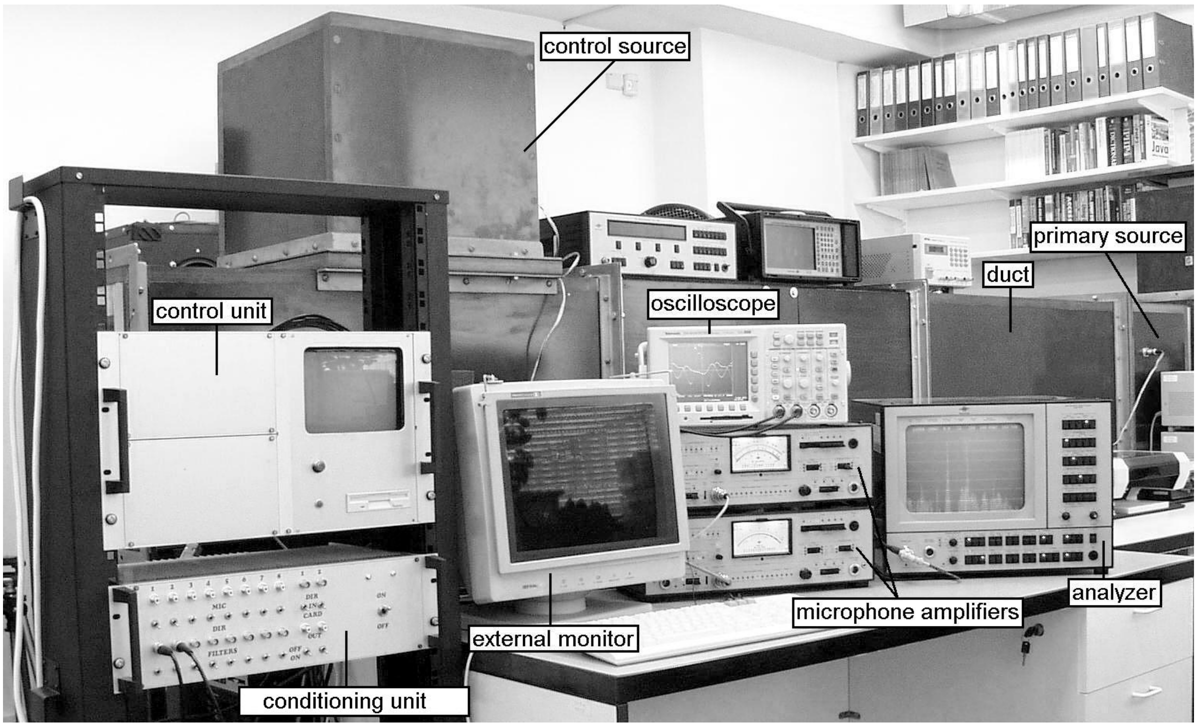

Fig. 10. The laboratory stand.

The main part of the laboratory stand is a 3-meter long acoustic duct. An internal cross-section is a square of 56cm x 56cm. The duct is made of heavy and stiffness material 2.5cm thick and has a 5cm thick lining of damping material.
A block diagram of the experimental setup is shown in *Fig. 11*.

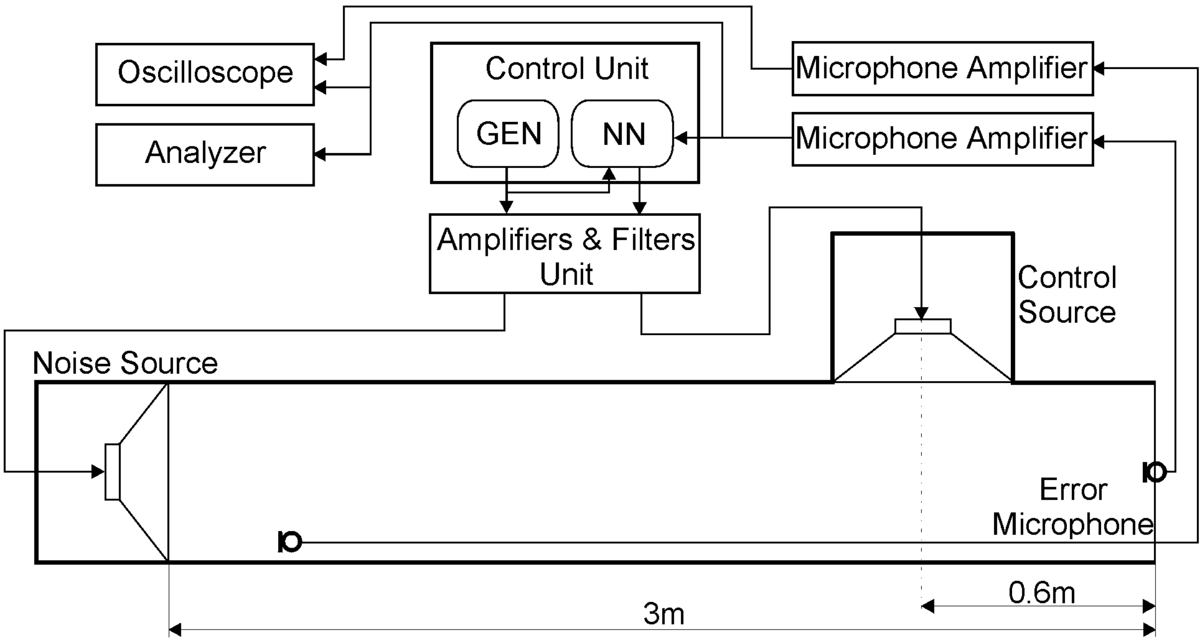

Fig. 11. The block diagram of the experimental setup.

The error microphone is placed at the end of the duct, 0.6m from the axis of symmetry of the control source. Microphones, microphone amplifiers and analyzer manufactured by Brüel & Kiær were used in the experiment. Noise signals were generated internally by the control unit.

The noise level at the end of the duct was set to 100dB. The reference signal of the neural network (NN) was taken directly from noise generator.

During the experiments, different types of noise signal and different numbers of neurons in the network were considered. The upper frequency limit of the properly working system was 200Hz. The most complex neural network implemented had twenty neurons in the input layer and three neurons in the hidden layer.

Experiments were made for sinusoidal noise signal. The frequency of noise signal was changed from 60Hz to 200Hz with 5Hz step. Inside this frequency, the range system was stable and achieved active reduction was 45dB. For almost all frequencies noise was reduced to the level of environment noise. The results of these experiments are shown in *Fig. 12*.

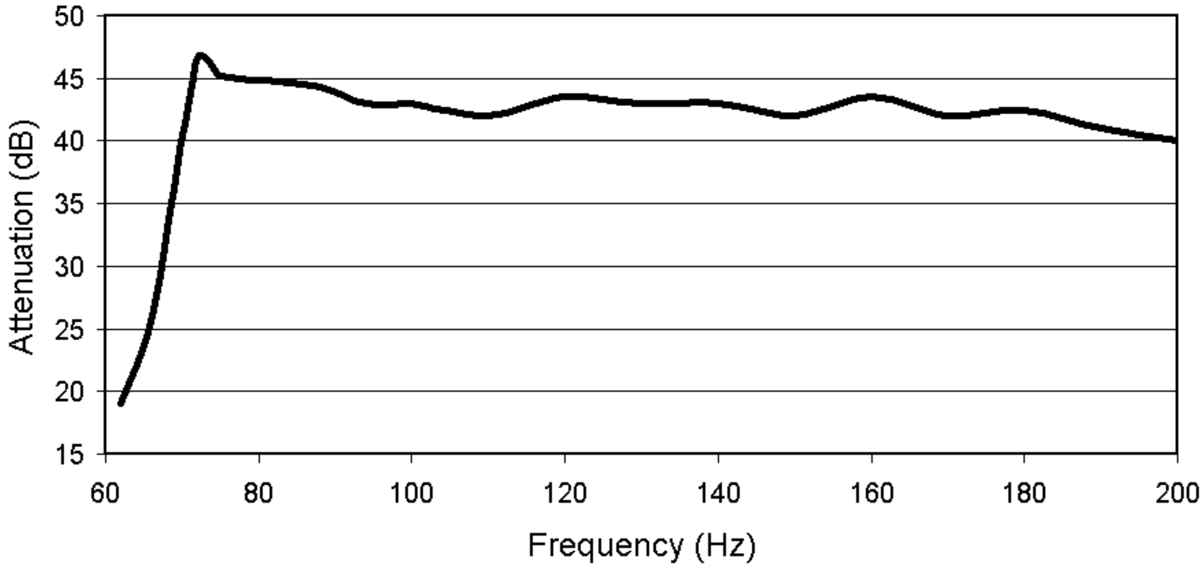

Fig. 12. The attenuation of the active system for sinusoidal noise signal.

In the next experiments the noise signal was a sum of two or three sinusoidal signals. In this case the stability of the system was maintained only when the frequencies of signals were not too distant from each other. It is caused by the influence of the error path transfer function not considered in the adaptation algorithm.

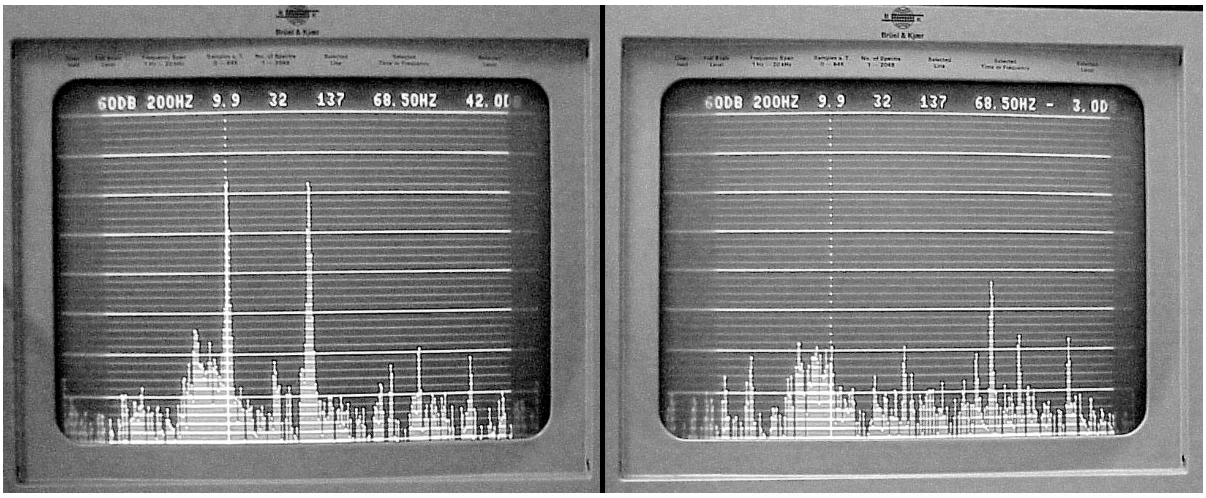

Fig. 13. Power spectra of the error signal before (left) an after (right) activating of the ANC system.

Fig. 13 illustrates behavior of the system while reducing noise signal consisting of two sinusoidal signals (69Hz and 103Hz). Both signals are reduced to the level of environment noise.

CONCLUSIONS

We have shown that the neural network-based ANC system can be build using a low-cost PC-based control unit without dedicated and expensive DSP processors. Experiments proved the usefulness of this system. A neural network consisting of twenty neurons in the input layer and three neurons in the hidden layer with a back propagation algorithm was implemented. Reduction up to 45dB for sinusoidal noise signal of frequency in the range from 60Hz to 200Hz was achieved. Significant reduction of two sinusoidal signals whose frequencies were not too distant was also obtained.

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