ARCHIVES OF ACOUSTICS
32, 4, 839–849 (2007)

APPLICATION OF GENETIC ALGORITHM IN AN ACTIVE NOISE CONTROL SYSTEM

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(*received October 02, 2006; accepted June 21, 2007*)

An active noise control (ANC) system utilizing a genetic algorithm for reduction of noise in duct is described. A continuous genetic algorithm with a heuristic crossover method was applied in the controller of the system. The ANC system was tested on a laboratory stand. Measurements of the efficiency of the system related to basic parameters of the genetic algorithm were performed. A comparison of the effectiveness of ANC system based on the genetic algorithm to the system based on the LMS algorithm is presented.

Keywords: genetic algorithm, active noise control, active noise reduction, crossover, LMS algorithm.

Notations

ANC	active noise control,
$b_{\mathrm{descendant}}$	coefficient of a descendant filter or gene of descendant's chromosome,
b_{parent}	coefficient of the parent filter or gene of parent's chromosome,
FIR	finite impulse response,
LMS	least mean squares,
β	mixing value for continuous parameter crossover.

1. Introduction

The principle of operation of the ANC system is based on the synthesis of a compensating signal with such amplitude and phase parameters that, as a result of its superposition with a noise signal, their mutual compensation occurs. The controller of an ANC system is responsible for the correct synthesis of the compensating signal. A digital filter is the main element of the controller. The task of the controller is setting the values of the digital filter coefficients in such a way that a maximum noise reduction is achieved. Classical adaptive controllers use different variations of a gradient algorithm [1]. In order to find the optimal form of a digital filter, a genetic algorithm [2] can be used.

Genetic algorithms are algorithms of searching a best solution of a given problem utilizing natural selection mechanisms known from the nature [3]. The distinguishing features of a genetic algorithm are: efficiency, easiness of adaptation to different requirements and simplicity of implementation. Since the useful procedures of implementing functions of genetic algorithms were developed, they have found all around interest of researches engaged in optimization problems [6, 7]. The possibilities of a genetic algorithm can be utilized in digital active noise control (ANC) systems [8–11]. Genetic algorithms can be used to calculate optimal parameters and positions of sensors and actuators of ANC systems [12, 13] as well as to optimisation of the adaptive filters of ANC systems [1]. The first area of application is growing rapidly along with the growing popularity and availability of so-called smart materials [14] served as sensors and actuators. The development of the second area of application is caused by the increasing computation possibilities of controllers applied in ANC systems.

The aim of this study was to elaborate an ANC system based on a genetic algorithm and verify it's efficiency in comparison with an ANC system utilizing the classical least mean square (LMS) algorithm.

2. Active noise control system based on the genetic algorithm

A controller based on a digital finite impulse response (FIR) filter is the basic element of an ANC system. Before launching the ANC system, the population of n filters represented by the filter coefficient vectors (otherwise chromosomes) has to be created. From the filter population, successive chromosomes are derived and then inserted into the ANC system controller as coefficient vectors of the FIR filter. For each chromosome its fitness is calculated on the basis of error signal measurements. The error signal represents the cancelled noise – a higher the error signal means lower efficiency of the ANC system and, at the same time, lower fitness of the implemented filter. When the whole population is verified, values representing the quality (fitness) are assigned to all chromosomes. Depending on the specific formula, the fitness influences the probability of duplication of the chromosome in the next population. In this way the fitness decides if the filter is selected to the next population or not. Filter duplication is related to the selection and crossover operation.

There are many selection methods which can be used to choose subjects participating in the crossover operation. The most popular is the selection based on the so-called roulette principle in which the probability of the subject selection is proportional to its fitness. As a result of the crossover operation a new population (new set of digital filters) is created and then the whole process is repeated. Considering the fact that the probability of selection of the filter for the crossover operation is greater when the error signal (measured while this filter is implemented in the controller of the ANC system) is smaller in following generations, populations of filters with better and better adaptation are formed, i.e. filters which enable a better noise reduction. When the genetic algorithm is stopped, coefficients of the best (optimal) filter are applied in the controller of the ANC system. To compare the efficiency of the ANC system based on a genetic algorithm with an ANC system based on a gradient algorithm, the well known LMS algorithm was implemented in the controller. This algorithm is activated with the filter which coefficients were calculated by the genetic algorithm.

A very important element influencing the functioning of a genetic algorithm is a method of parameters coding. The most widely used classification of genetic algorithms divides them in binary and continuous algorithms. The selection of the coding method strongly influences the realisation of the crossover operation. When the binary coding is used, genes exchange ensures that the whole parameters space is analysed. The dimensions of the parameter space are limited only by the number of bits applied in coding. When the continuous coding is used, the crossover method analogous to that used in binary coding is not effective and does not give proper results. First of all, because one gene represents the whole parameter, a one-point crossover is usually not sufficient. It results from the fact that for the same optimisation problem a continuous chromosome is much shorter than its binary equivalent and the accuracy of the searching parameters space (during the crossover operation whole groups of parameters are exchanged) is much lower. To solve this problem, continuous genetic algorithms utilize a multipoint crossover. In the boundary case, the number of crossover points equals the number of parameters.

Another problem arises from the invariability of parameters. In successive generations, the values of parameters stored in the particular genes are not modified but change only their location in the chromosome. In this way, in spite of the continuous parameters space, during the operation of a genetic algorithm, the ANC system has to its disposal only a limited set of digital filters. The best filter from this set can differ considerably from the optimal form. This problem can by partly solved using the mutation operation. This operation should be implemented very rarely (low probability of appearance), thus relying exclusively on this mechanism has no practical application. In this situation more complex methods of calculation of crossed parameters (genes) were elaborated [4, 8]. As the result of genes exchange, they make it possible to create parameter values that do not exist in parent chromosomes.

The principle of the genetic algorithm hinder the using of its adaptation possibilities during the work of the ANC system. In each ANC system based on the genetic algorithm two phases of activity can be distinguished. The first one is the process of finding an optimal filter which constitutes the best form of the controller. During this phase the ANC system does not work. It is used to process the evolution functions based on chromosomes built of coefficients of digital filters. At the moment of finding the optimal filter, the ANC system is switched to a second phase of activity. Parameters of the optimal filter are stored in the controller and the ANC system is started as a classical system. In this phase, the ANC system can have or not have adaptive possibilities.

3. Laboratory stand

For testing the ANC system based on the genetic algorithm, an active system of reduction of noise propagating in a duct was used. The schematic diagram of the laboratory stand is presented in Fig. 1. The ANC system consists of an acoustic duct, two loudspeakers working as primary and secondary sources, an error microphone, amplifiers (Amp1 and Amp2), two generators (Gen 1 and Gen 2) and a digital controller. A continuous genetic algorithm (GA) with a heuristic crossover method was applied in the controller. The crossover operation is described by the formula (1).

$$\begin{aligned} b_{\text{descendant1}} &= b_{\text{parent1}} - \beta\left(b_{\text{parent1}} - b_{\text{parent2}}\right), \\ b_{\text{descendant2}} &= b_{\text{parent2}} + \beta\left(b_{\text{parent1}} - b_{\text{parent2}}\right). \end{aligned} \tag{1}$$

Each descendant parameter, $b_{\text{descendant1}}$ and $b_{\text{descendant2}}$, was calculated on the basis of the values of parent parameters b_{parent1}, b_{parent2} and the coefficient β (the so-called mixing value for the continuous parameter crossover). In accordance with (1), the choice

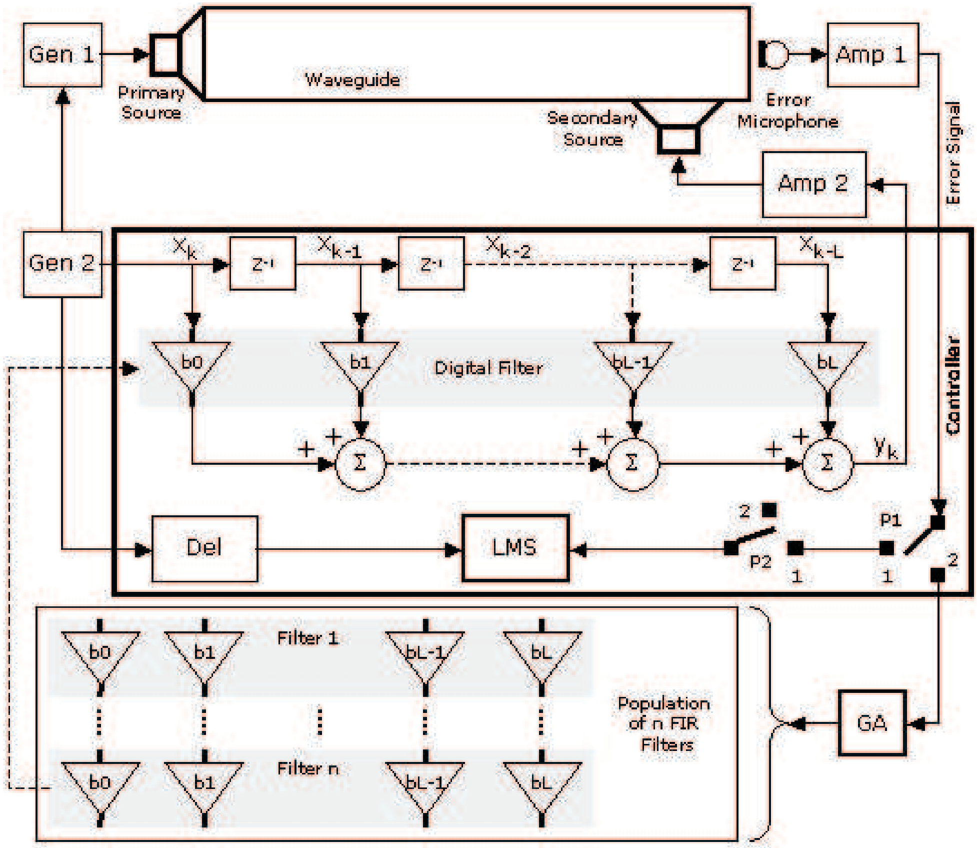

Fig. 1. Block diagram of the ANC system.

of the β coefficient value enables the generation of values of descendant parameters located between the values of patents' parameters ($\beta = 0 \ldots 1$) or outside these values ($\beta > 1$).

To compare the effectiveness of a genetic algorithm and a LMS algorithm, the controller has also the ability to operate according to this algorithm represented by the block denoted by LMS in Fig. 1. The digital delay line (Del in Fig. 1) is implemented in the controller to compensate the secondary signal path [1].

The ANC system can be switched between three modes of operation (Fig. 1). In the first mode (switch P1 set to position 2), it uses the genetic algorithm. It enables the generation of filter coefficient vectors (chromosomes) and determines their fitness on the basis of the error signal. In the second mode (switch P1 set to position 1, switch P2 set to position 1), it works as an adaptive system based on the least mean squares algorithm. In the third mode (switch P1 set to position 1, switch P2 set to position 2), it works as a non adaptive ANC system. In the second and third modes, at the moment of activation of the system, the coefficients of the digital filter are copied from the optimal filter form calculated during the first mode of operation.

During the laboratory experiments, the compensated signal (noise) was generated digitally by the software implemented in the controller. The structures of the generators (Gen 1 and Gen 2 in the Fig. 1) are presented in Fig. 2.

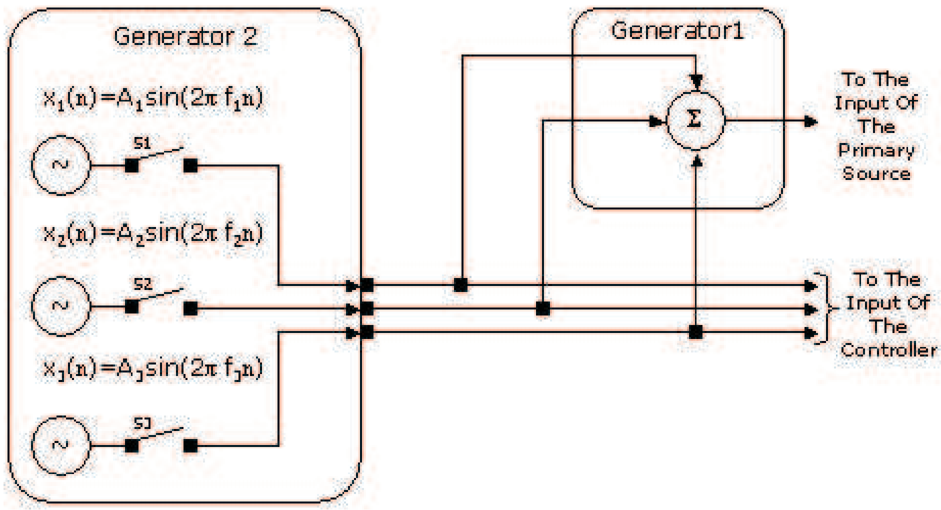

Fig. 2. The structure of the compensating signal generator.

Three sinusoidal signals are calculated internally by the controller. The sum of them is used to power the primary source. Independent signals (without summing operation) are used do synthesize the compensating signal. In this way, the controller can control every single component included in the compensated signal.

4. Results of the measurements

Before the measurements of effectiveness of the ANC system, some preliminary measurements verifying the procedure of estimating the fitness of the filter embedded in the controller were performed. Because the fitness depends directly on the amplitude of the error signal and thereby to the cost (inverse of a fitness), the verifying procedure was based on cost measurements. As an example, the results of cost measurements are presented in Fig. 3. To ensure a correct cost measurement in the software implemented to the controller, the possibility to define the times of the error signal measurements was added. This enables the following way of the error signal measurement: the system is activated, then after a defined time, the error signal is measured and then the measurement procedure is stopped after a defined time period. All times are represented by the number of signal samples. The results of measurements presented in Fig. 3 were obtained for the following parameters:

- population size (number of filters/chromosomes): 4,
- filter length: 16,
- sample rate: 5000 Hz,
- frequency of the sinusoidal error signal: 100 Hz,
- length of the measured signal: 500 samples (start: 3500 samples – stop: 4000 samples).

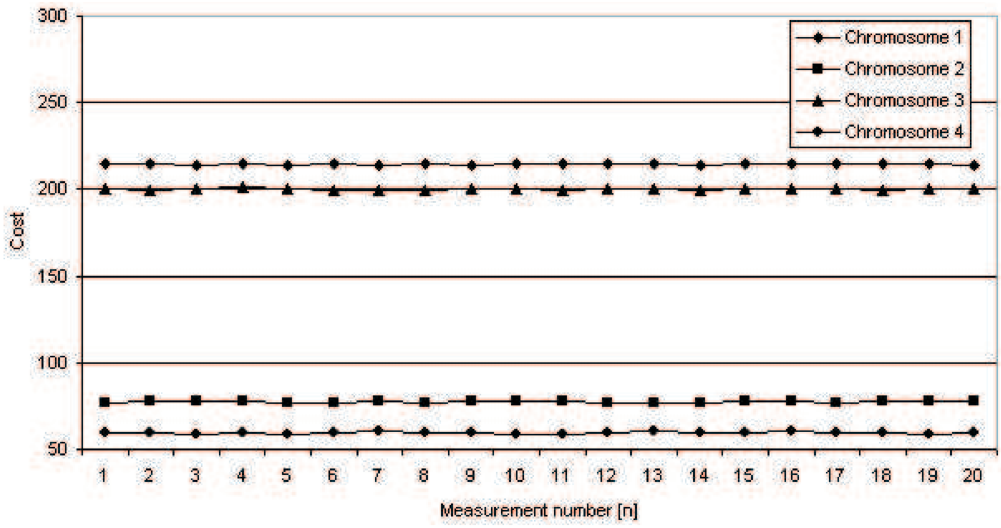

Fig. 3. Results of cost measurements performed on the basis of the error signal.

Proper evaluation of fitness/cost values on the basis of error signal determines the flawlessly functioning of the genetic algorithm. Detailed data obtained as a result of statistical analysis of cost values from Fig. 3 are presented in Table 1.

Table 1. Results of statistical analysis of cost values calculated from error signal values.

Parameter	Chromosome 1	Chromosome 2	Chromosome 3	Chromosome 4
Mean value	210.3	77.00	200.65	62.15
Standard deviation	0.571241	0.561951	0.67082	0.48936
A 95% level of confidence	0.249809	0.245426	0.293635	0.214748

As one can see, the applied measurement system ensure a correct estimation of the filter fitness. Of course, there is a small possibility of the event that during the operation of the ANC system, a temporary disturbance (for example acoustic signal which is not correlated with compensated one generated by the noise source) can cause that a good filter is classified as a low fitness filter and will be eliminated from the descendant population. Since the genetic algorithm is resistant, this causes only a short time disturbance of its operation. The carried out experiments proved it.

After fixing the controller parameters which ensure the correct estimation of fitness, the measurements of the effectiveness of the ANC system based on the genetic algorithm were carried out. The results of measurements are presented in Figs. 4–7. A 100-Hz tonal signal and its harmonics (200 Hz and 300 Hz) were used as a compensated noise. Such form of the noise was intentionally selected for the potential utilization of the ANC system to reduce the noise emitted by a power transformer. Transformer is a good example of low frequency stationary noise source. Values of active noise reduction

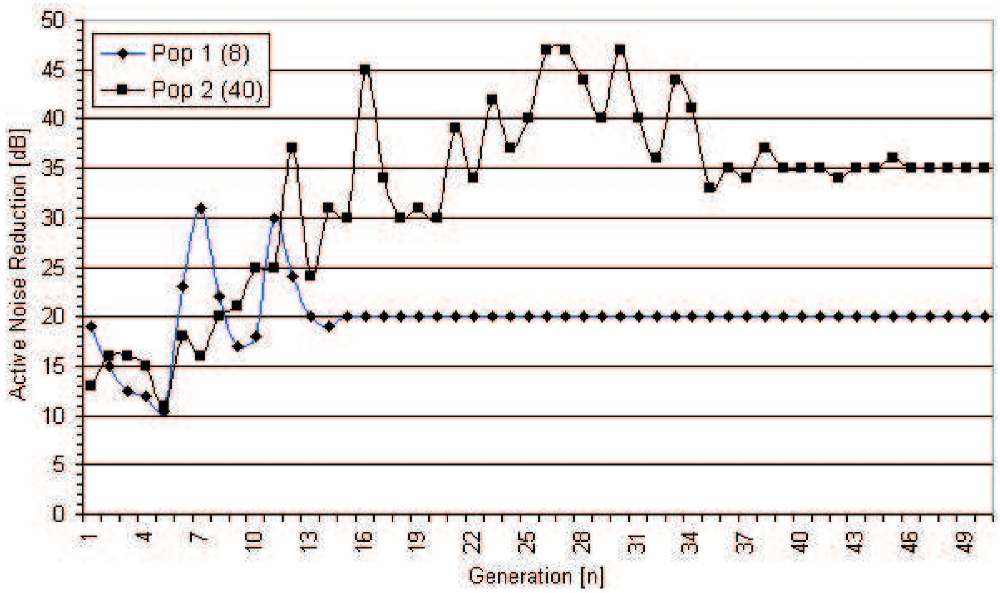

Fig. 4. The influence of the number of filters/population size (Pop 1 $=$ 8 and Pop 2 $=$ 40) on active reduction of the 100 Hz tonal signal (excitation signal: 100 Hz, filter length: 16, crossover probability: 0.6, mutation probability: 0.001).

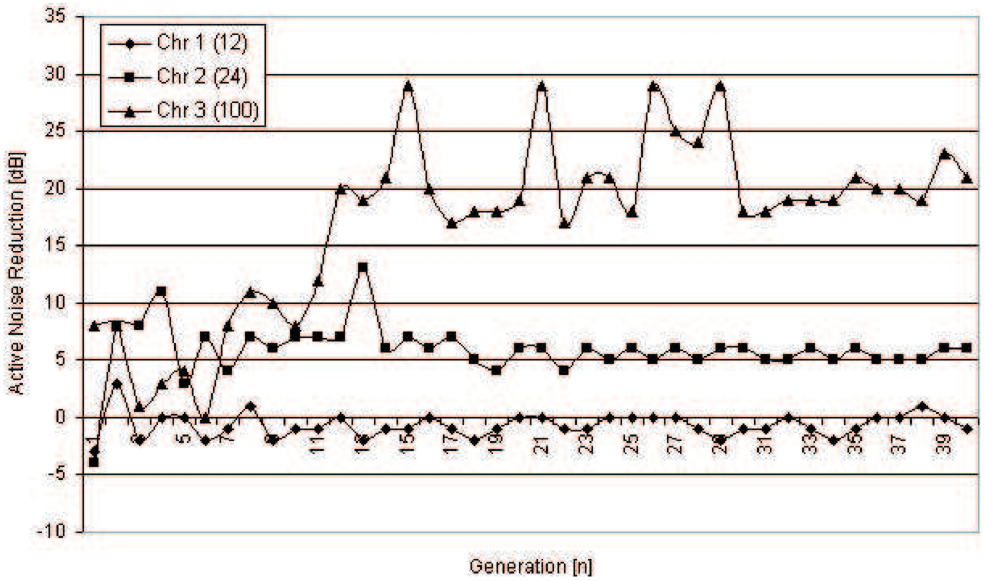

Fig. 5. The influence of the filter length (chromosome length) on the active reduction of the 100 Hz tonal signal (excitation signal: 100 Hz + 200 Hz, number of filters: 40, crossover probability: 0.6, mutation probability: 0.001).

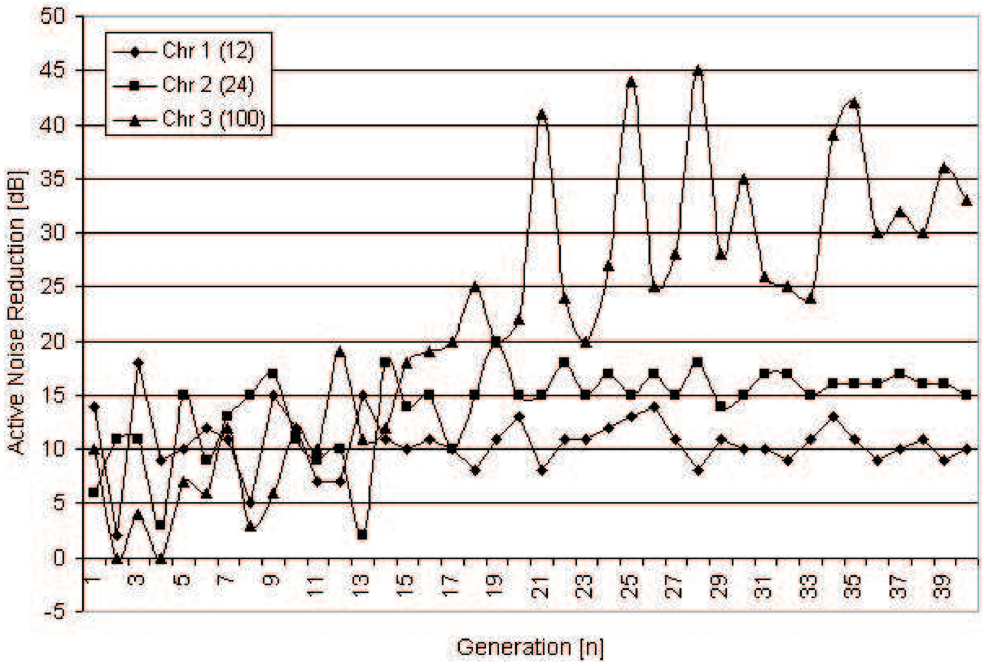

Fig. 6. The influence of the filter length (chromosome length) on the active reduction of the 200 Hz tonal signal (excitation signal: 100Hz + 200 Hz, number of filters: 40, crossover probability: 0.6, mutation probability: 0.001).

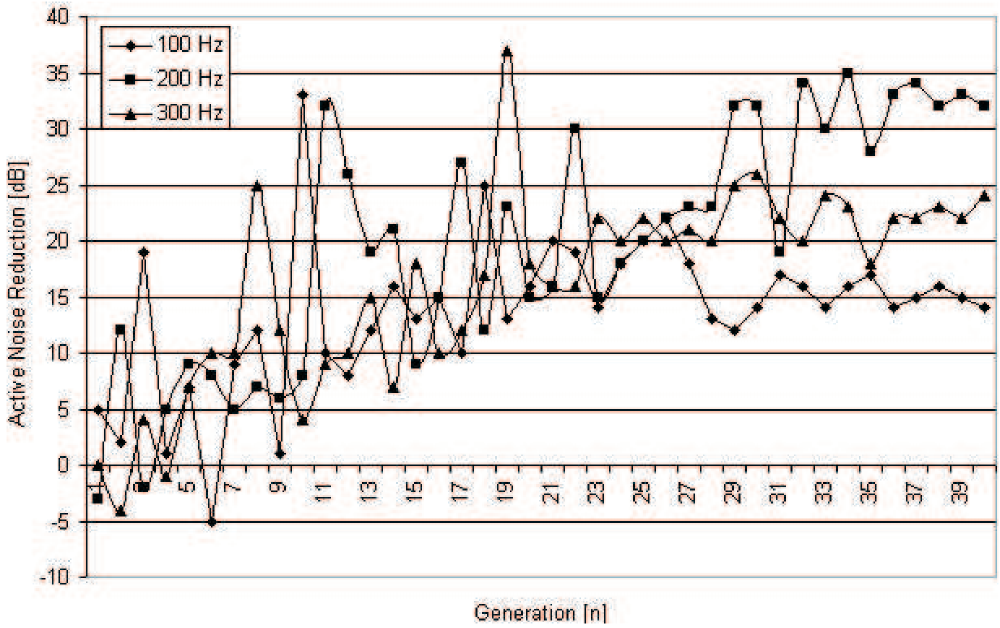

Fig. 7. Active reduction of the signal consisting of three tonal components (excitation signal: 100 Hz + 200 Hz + 300 Hz, number of filters: 40, filter length: 100, crossover probability: 0.6, mutation probability: 0.001).

were measured for each harmonic component independently. Active noise reduction or effectiveness of the ANC system was defined as a difference between the noise level without and with the presence of working ANC system.

Results of measurements in the case of a simple tonal noise signal are presented in Fig. 4. When the calculated optimal filter was applied in the system based on least mean squares adaptation algorithm increasing of the effectiveness was observed and noise was reduced by 45 dB to the level of the background. Concluding – the gradient algorithm was better than the genetic algorithm.

Results of measurements in the case of more complex compensated signal composed of two tones (100 Hz and 200 Hz) are presented in Fig. 5 and Fig. 6. The genetic algorithm operating on 40 digital filters of the lengths from 12 to 100 was used in the experiment.

For the filters of length 12, the ANC system was able to reduce only the component of 200 Hz (Fig. 6). The effect of active reduction of the 100 Hz (Fig. 5) component was not observed. This was caused by the insufficient chromosome length applied in the digital filter. When the calculated optimal filter was applied in the system based on the least mean squares adaptation algorithm, no difference in the effectiveness was observed. Concluding – the gradient algorithm was as good as the genetic algorithm one.

In Fig. 7, the results of measurements of the active reduction of the composite signal is presented. The compensated signal consists of three tonal components of 100 Hz, 200 Hz and 300 Hz. For the filter of the length 100 (chromosome with 100 genes), it is possible to reduce all three components at the same time. From the generation number 25, the active noise reduction is about 20 dB.

When the calculated optimal filter was applied in the system based on least mean squares adaptation algorithm, a progressive deterioration of the effectiveness was observed and, after a short time, the ANC system lost its stability. Concluding: the gradient algorithm was worse than the genetic algorithm one.

The measurement results presented prove the advantages connected with the utilization of the genetic algorithms in the ANC systems. Particularly, the important advantage is the possibility of the active reduction of noise without the prior knowledge of the parameters of the secondary error path. For compound noise signals and relatively a simple controller structure, the genetic algorithm enables a proper operation of the ANC system, while the gradient algorithm based system becomes unstable.

5. Conclusions

In spite of numerous advantages of classical ANC systems, they are very sensitive to an improper controller structure. Assuming a wrong filter type, a too low or too high filter order, an inaccurate representation of the transmittances found in the system, not regarding the influence of the so-called secondary signal path, are the reasons that designing an ANC system is very difficult and is a complicated process. Applying the genetic algorithm can simplify this process.

A very important issue related to the implementation of a genetic algorithm in ANC systems working in real conditions is the proper determination of the fitness value which represents the quality of the controller. Because of disturbances in real conditions, a direct implementation of simulation algorithms is not recommended. The results of measurements proved that the measurement of an error signal has to be broadened by appropriate protection against improper fitness/cost determination. In the elaborated ANC system, this problem was solved by a rigorous selection of the time of measurement of the error signal amplitude. The results of measurements verified positively this approach.

The ANC system described makes it possible to reduce the sound pressure level for tonal signals by 35 dB, for two tonal signals by 20 dB to 30 dB and for signals consisting of three tonal components by 15 dB to 30 dB for all components simultaneously. For simple tonal signals, the efficiency of the ANC system based on a genetic algorithm is lower than the effectiveness of a classical ANC system utilising a gradient algorithm. For such signals, the genetic algorithm can be used as a preliminary optimisation algorithm started before the gradient algorithm to determine default values of the digital filter coefficients. More exact values of these coefficients can be calculated using the gradient algorithm. For more complex noise signals and simple controller structures, systems based on genetic algorithms are more effective than the classical ANC systems.

Acknowledgments

This publication has been prepared within the framework of disseminating the results of the National Programme "Adaptation of Working Conditions in Poland to European Union Standards" supported in the years 2005–2007 by the Ministry of Education and Science within the scope of research and development, and by the Ministry of Labour and Social Policy within the scope of state services. The Central Institute for Labour Protection – the National Research Institute was stated the Programme's main coordinator.

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