GENETIC ALGORITHM APPLICATION FOR ELECTRO-DYNAMIC TRANSDUCER MODEL IDENTIFICATION

Denys Volkov[1]✉, ***Artem Zubkov***[2], ***Vitalii Didkovskyi***[3]
[1]Department of Acoustic and Multimedia Electronic Systems, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine
ORCID: http://orcid.org/0000-0002-7838-5049
[2]Department of Acoustic and Multimedia Electronic Systems, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine
ORCID: http://orcid.org/0000-0001-8850-0023
[3]Department of Acoustic and Multimedia Electronic Systems, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine
ORCID: https://orcid.org/0000-0002-0807-822X
✉Corresponding author: Denys Volkov, e-mail: denys@volkov.in

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ABSTRACT

Research object: the adaptation and application of the genetic algorithm for electrodynamic transducer model parameters identification.
Investigated problem: to formulate loudspeaker identification task as an optimization problem, adapt it to the genetic algorithm framework and compare obtained results with classical identification method using added mass.
Main scientific results: the complete genetic algorithm loudspeaker identification procedure is presented, including:
– data acquisition scheme, where the directly measured values for the algorithm application are: voltage at loudspeaker terminals, current through the voice coil and displacement of the moving part
– selection of an appropriate set of genes of an individual
– derivation of the fitness function for assessing the quality of the identified parameters, which can also be used to identify other types of electroacoustic transducers
Also, the advantages of this method in comparison with the classical method of identification using added mass are considered, that are its versatility and ability to quickly configure and adapt for research and experimentation with different loudspeaker models and different types of transducers used in acoustics.
Area of practical use of the research results: the proposed genetic loudspeaker model identification scheme can be directly applied on practice to speed up research and development tasks in electroacoustics and other related fields that require frequent experimentation with different types of transducer models.
Innovative technological product: genetic algorithm based loudspeaker identification scheme that can be applied to identify various model of electrodynamic transducers.
Scope of application of the innovative technological product: electroacoustics, loudspeaker design, audio systems.

1. Introduction

1. 1. The object of research

The object of research of presented work is to develop a loudspeaker identification scheme using genetic algorithm and compare obtained result with widely used added mass method. Furthermore, to show genetic algorithm flexibility and demonstrate how it can be adapted to identify more complicated loudspeaker models.

1. 2. Problem description

Genetic algorithm is an optimization method that belongs to a group of evolutionary algorithms – meta-heuristic optimization based on competition of individuals within the population for several epochs. These algorithms are based on the principles of evolution that were borrowed from nature. That is why many terms used in genetic and evolutionary algorithms have been borrowed from biology (i.e. individual, population, recombination, mutation, etc.). Usually, these algorithms are used for problems where the classical optimization methods are not applicable: large amounts of data, data is noisy, loss function cannot be described analytically or it is very complex, loss function is not differentiable, simultaneous optimization of large parameter number, logic problems and others [1].

The first attempts to simulate natural evolution were made in the 1950s by the scientists Nils Baricelli and Alex Fraser [2, 3]. Their works contained the foundations of modern genetic algorithms. In the 1960s, the ideas of Barrichelli and Fraser became widely known and attracted attention of many scientists and researchers. During these years, genetic algorithms were first used to solve real practical engineering problems that could not be solved by other methods. In the early 1970s, genetic algorithms became especially popular due to the works of American scientist John Henry Holland, who is now known as the "father" of genetic algorithms. In his book "Adaptation in natural and artificial systems" [4], he introduced a formalized mathematical apparatus that has extended the application of genetic algorithms and is widely used by modern scientists. However, the research in the field of genetic algorithms remained more theoretical until the mid-1980s, as a large number of calculations took a long time and required powerful computers. Beginning in the 1990s, along with the growth of computational power, genetic algorithms began to be actively used in practice to solve a variety of problems, from the identification of physical systems to artificial intelligence.

The problem of loudspeaker model parameter identification can be represented as an optimization problem. With this formulation, the optimal model parameters are those that provide simulated loudspeaker responses as close as possible to measured ones. The classical loudspeaker identification method is the method of added mass [5] which is simple and easy to use on practice. But its significant disadvantage is that it allows to identify parameters of only a simple model of an electrodynamic transducer, the accuracy of which is often not enough for research and development purposes. The other group of methods requires an additional measurement of one of the mechanical states of a loudspeaker, such as membrane velocity, displacement or acceleration [6]. These methods are usually more robust and can be applied to small and fragile loudspeakers, where the addition of extra mass to the membrane is not possible. Genetic algorithm based identification method also requires to measure a loudspeaker mechanical state. In our case, it is membrane displacement that was measured with a laser.

1. 3. Suggested solution to the problem

Despite most loudspeaker models can be expressed analytically and allow to use classical identification methods, the genetic algorithms application for these purposes is of great scientific interest. First, modern electrodynamic transducer models require complex identification technics, which development require significant amount of time separately from the model development itself. Second, genetic algorithm application allows to develop a single universal identification scheme that will be mostly model-independent and will allow to quickly experiment with different models without spending additional time developing specialized identification algorithms.

The aim of research described below is to formulate loudspeaker identification task as an optimization problem, adapt it to the genetic algorithm framework and compare obtained results with classical identification method using added mass.

2. Materials and Methods

2. 1. Genetic algorithm description

Genetic algorithm is used to solve optimization and modeling problems by sequential selection, combination and variation of the desired parameters using mechanisms that resemble biological evolution. A main feature of the genetic algorithm is the emphasis on the "crossover" operator usage, which performs the operation of recombination of candidate solutions, similar to the individual crossover in nature. The common genetic algorithm block diagram is presented in the **Fig. 1**.

The problem is encoded in such a way, that solution can be represented as an array of chromosome-like information. The element of such array is often simply called "chromosome". Some finite number of single chromosomes forms a candidate solution, called "individual", and a finite number of individuals form a "population". Each individual in a population is evaluated using a fitness function (similar to the cost function). As a result, each individual is assigned a certain fitness value, which determines the probability for this individual to pass its chromosomes to the next generation. After that, using obtained fitness values, several individuals are chosen to proceed to crossover and mutation operations and form new generation. Next generation individuals are also evaluated using same fitness function and selection and mutation genetic operations are performed. This simulates an evolutionary process that lasts several life cycles ("generations") until the stopping criterion for the algorithm is reached. This criterion can be:

– convergence to the optimal solution;
– reaching a predetermined number of generations;
– reaching a time limit for the algorithm to run.

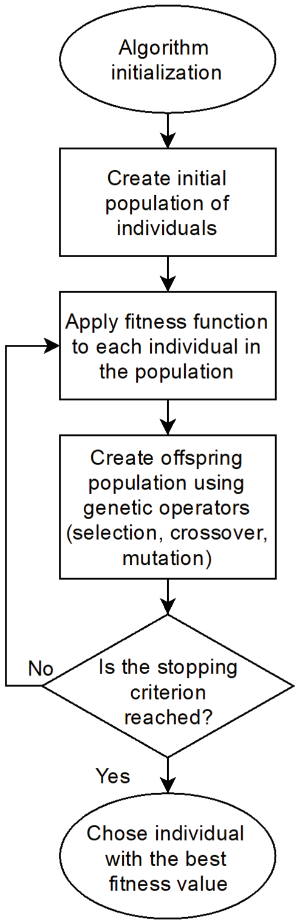


Fig. 1. Genetic algorithm implementation block diagram

2. 2. Algorithm adaptation

The main steps of the genetic algorithm remain mostly unchanged regardless of the task. Algorithm implementation to the real problem is performed through the assignment of chromosomes to real physical quantities and parameters of the model, and through the fitness function design.

In our case, we are searching for the model parameters of a typical two-inch electrodynamic transducer, shown in **Fig. 2**.

The data required to run the algorithm and identify the model was obtained using a measuring setup according to the scheme in **Fig. 3**.

The measured values are: $x(t)$ – displacement of the moving part, $e(t)$ – voltage (equivalent to the voltage at loudspeaker terminals), and $i(t)$ – current (equivalent to the current through loudspeaker voice coil).

The first step in adapting the genetic algorithm to our task is to choose the transducer model whose parameters need to be identified. To begin with, a simple linear model shown in **Fig. 4** was chosen.

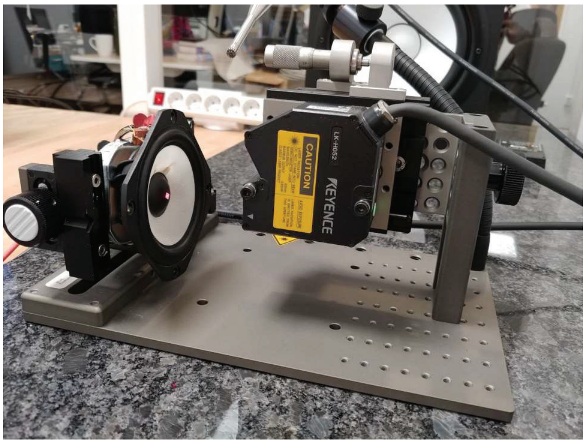


Fig 2. 2-inch electrodynamic transducer under study

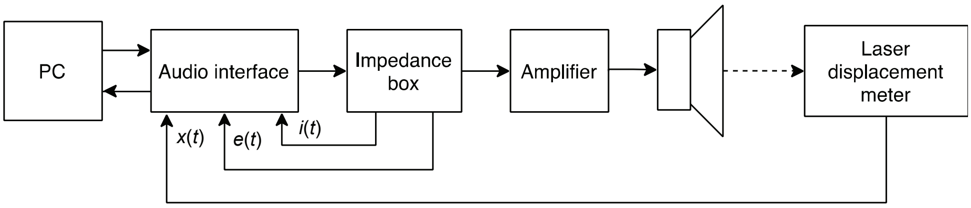


Fig. 3. Measurement setup

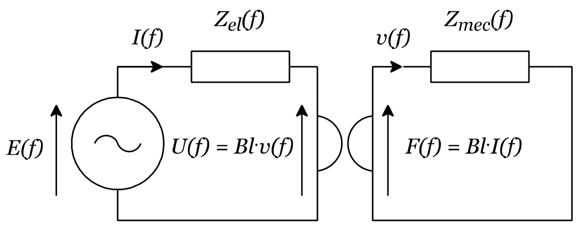


Fig. 4. Electro-mechanical model of an electrodynamic transducer: $E(f)$ – voltage at the loudspeaker terminals (V); $I(f)$ – current through the voice coil (A); Bl – force factor (T*m); $F(f)$ – force, acting on the moving part (N); $V(f)$ – velocity of the moving part (m/s); $U(f)$ – back electromotive force (V)

Impedances $Z_{el}(f)$ and $Z_{mec}(f)$ are respectively: electrical impedance of the voice coil and mechanical impedance of the moving part, which can be written as:

$$Z_{el}(f) = R_e + j \cdot 2\pi \cdot f \cdot L_e, \tag{1}$$

$$Z_{mec}(f) = R_{ms} + j \cdot 2\pi \cdot f \cdot M_{ms} + \frac{K_{ms}}{j \cdot 2\pi \cdot f}, \tag{2}$$

where f – frequency of an input signal (Hz);
R_e – voice coil DC resistance (Ohm);
L_e – voice coil inductance (Hn);
R_{ms} – mechanical resistance (kg/s);
M_{ms} – moving mass (kg);
K_{ms} – suspension stiffness (N/m);
j – complex one.

At the second step, it is necessary to determine which parameters will act as chromosomes. In our case, to begin with, let's take all the unknown parameters of the model from the equations (1) and (2) and the force factor Bl as the individual chromosomes:

$$I = \left[R_e, L_e, Bl, R_{ms}, M_{ms}, K_{ms}\right]. \tag{3}$$

Lastly, it is necessary to derive a fitness function that will objectively determine how much one individual is better than another. To do this, let's first compose the equations that describe the model behavior in frequency domain (will use circular frequency ω=2π*f*):

$$E(\omega) = R_e I(\omega) + j\omega L_e I(\omega) + BlV(\omega), \tag{4}$$

$$Bl \cdot I(\omega) = j\omega M_{ms} V(\omega) + \frac{K_{ms}}{j\omega} V(\omega) + R_{ms} V(\omega). \tag{5}$$

Equation (4) describes transducer behavior in electrical subsystem and equation (5) – in mechanical subsystem. From these equations, it is possible to express the total input electrical impedance $Z_{tot}(\omega)$ and mechanical impedances $Z_{mec}(\omega)$ as follows:

$$Z_{tot}(\omega) = \frac{E(\omega)}{I(\omega)} = R_e + j\omega L_e + Bl\frac{V(\omega)}{I(\omega)}, \tag{6}$$

$$Z_{mec}(\omega) = Bl\frac{I(\omega)}{V(\omega)} = j\omega M_{ms} + \frac{K_{ms}}{j\omega} + R_{ms}. \tag{7}$$

Now, in equations (6) and (7) let's separate the values that can be directly measured from the model parameters:

$$\frac{E(\omega)}{I(\omega)} = R_e + j\omega L_e + \frac{Bl^2}{j\omega M_{ms} + \frac{K_{ms}}{j\omega} + R_{ms}}, \tag{8}$$

$$\frac{V(\omega)}{I(\omega)} = \frac{Bl}{j\omega M_{ms} + \frac{K_{ms}}{j\omega} + R_{ms}}. \tag{9}$$

Now in equations (8) and (9) all measured values are on the left side and model parameters are on the right side, so it is possible to compare these sides to calculate modeling error and use this value as a fitness function for the genetic algorithm:

$$E_1 = MSE_\omega\left[\frac{E(\omega)}{I(\omega)} - R_e - j\omega L_e - \frac{Bl^2}{j\omega M_{ms} + \frac{K_{ms}}{j\omega} + R_{ms}}\right], \tag{10}$$

$$E_2 = MSE_\omega\left[\frac{V(\omega)}{I(\omega)} - \frac{Bl}{j\omega M_{ms} + \frac{K_{ms}}{j\omega} + R_{ms}}\right], \tag{11}$$

$$E_{tot} = E_1 + E_2, \tag{12}$$

where MSE_ω – mean squared error over frequency

In this way, the E_1 value in equation (10) corresponds to the modeling error of the total input electrical impedance, and E_2 value in equation (11) – the modeling error of mechanical impedance. Total error E_{tot} from equation (12) will be used as the fitness function in the genetic algorithm.

Thus, the smaller the E_{tot} value, the better a particular individual fit the model and more likely that this individual will pass its chromosomes to the next generation. The algorithm will be repeated until the smallest possible modelling error is reached.

3. Results

Genetic algorithm described above was implemented on Python using the DEAP library [7] which contains the basic operators necessary for the genetic algorithm operation.

As it can be seen in **Fig. 5**, the minimum individual error and the average error over the whole population are rapidly decreasing and after several generations remain almost unchanged. Also, it is possible to see that the average error in the population is very close to the error of the best individual. This demonstrates that after a few generations, all individuals in the population are close to the optimal value. This rapid convergence of the algorithm indicates that the application of the genetic algorithm for our problem is possible, and that the chosen fitness function (equations (10)–(12)) is appropriate.

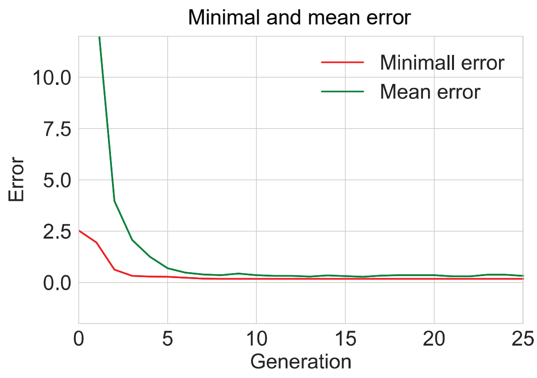


Fig. 5. Minimal and average error by generations

Fig. 6 shows the total input electrical impedance model using parameters found by the genetic algorithm. Also, the measured and added mass method based total input electrical impedances are presented for comparison.

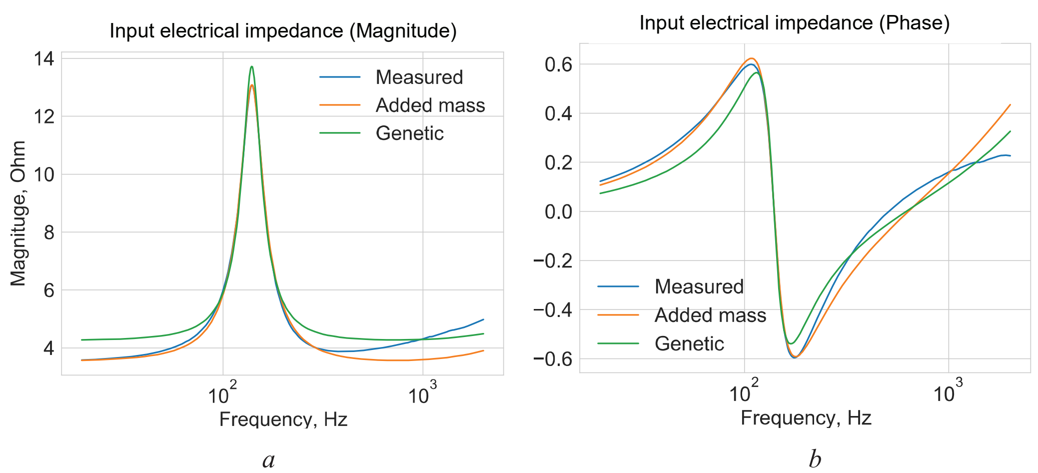
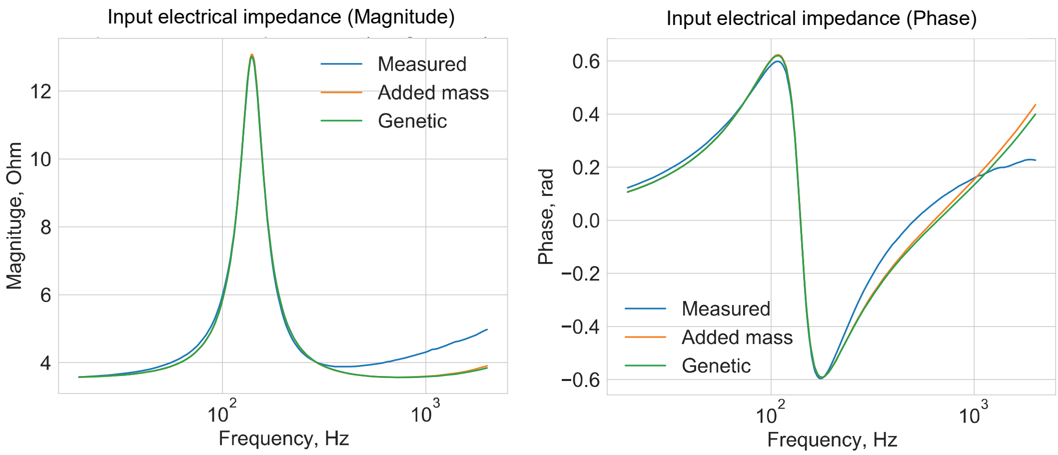


Fig. 6. Total input electrical impedance: *a* – modulus; *b* – phase

As it can be seen in the **Fig. 6**, the genetic algorithm has indeed found some parameters that bring the model response closer to the actual measured one. However, at frequencies below the resonance, the modeling error is quite significant, and simple added mass method shows much better approximation results than the genetic algorithm. To fix this, it was decided to exclude the voice coil DC resistance Re from the individual chromosomes (and, hence, from the optimization), and use manually measured value with an ohmmeter: *Re*=3.54 Ohms. The fitness function remains unchanged. Now our individual has one chromosome less:

$$I = \left[L_e, Bl, R_{ms}, M_{ms}, K_{ms}\right]. \tag{13}$$

Fig. 7 shows the total input electrical impedance behavior after the above described changes were applied.



a *b*

Fig. 7. Total input electrical impedance (experiment 2): *a* – modulus; *b* – phase

As it can be seen in the **Fig. 7**, after the voice coil resistance R_e was excluded from the optimization and manually measured value was applied, the model behavior at frequencies below the resonance was significantly improved, and its performance appear to be very close to the model identified by the added mass method. **Table 1** shows the comparison of the model parameters identified by the added mass method and using genetic algorithm.

Table 1

Comparison of identified model parameters

Parameter	Added mass method	Genetic algorithm
f_{res}, Hz	137.2	138
R_e, Ohm	3.54	3.54
L_e, H	1.39e-4	1.31e-4
Bl, T*m	2.43	2.43
M_{ms}, kg	2.7e-3	1.2e-3
K_{ms}, N/m	2.04e3	9.09e2
R_{ms}, kg/s	0.62	0.63

Table 1 shows that genetic algorithm has found the model parameters that are very close to those identified by the added mass method. Except for the moving mass M_{ms} and stiffness K_{ms}. these parameters randomly changed their values for each algorithm realization, although the error values remained equally low and the resulting graph of the modulus and phase of the total input electrical impedance was identical to the graph in **Fig. 7**. After further investigations, it was concluded that M_{ms} and K_{ms} parameters compensate each other, i.e. a larger M_{ms} value corresponds to a smaller K_{ms} value and vice versa. This leads to the fact that genetic algorithm cannot unambiguously identify these parameters, because with their mutual compensation, the resulting error will always remain low. To fix this problem, it was decided to exclude one of these parameters (M_{ms} or K_{ms}) from the individual chromosomes (hence, from the optimization) and instead express it using the other parameter and transducer resonance frequency, that can be found as the frequency at which the modulus of total input electrical impedance reaches maximum.

$$f_{res} = \max_f |Z_{tot}|, \tag{14}$$

$$K_{ms} = M_{ms} \cdot (2\pi \cdot f_{res})^2. \tag{15}$$

So now the individual has four chromosomes left:

$$I = \left[L_e, Bl, R_{ms}, M_{ms}\right]. \tag{16}$$

As expected, after the changes described above were implemented, the algorithm convergence and resulting error remained equivalent to the previous attempts, but the M_{ms} and K_{ms} values did not change randomly from one iteration to another and they became close to the parameters identified by the added mass method. **Table 2** shows the comparison of the model parameters identified by the added mass method and using genetic algorithm after the above describe changes were applied.

Table 2
Comparison of identified model parameters (second attempt)

Parameter	Added mass method	Genetic algorithm
f_{res}, Hz	137.2	138
R_e, Ohm	3.54	3.54
L_e, H	1.39e-4	1.31e-4
Bl, T*m	2.43	2.43
M_{ms}, kg	2.7e-3	2.8e-3
K_{ms}, N/m	2.04e3	2.1e3
R_{ms}, kg/s	0.62	0.63

Thus, it was shown that genetic algorithm is able to identify parameters of the electrodynamic transducer model shown in **Fig. 3** and described by equations (1) and (2). Although, the model parameters were found correctly, **Fig. 7** shows that at frequencies above the resonance, simulated total input electrical impedance phase and modulus do not completely follow the measured response. The same applies to the added mass method. This indicates a lack of accuracy of the used model and does not relate to the identification method.

In order to improve the model behavior at higher frequencies, it was decided to use a little more complicated model of the loudspeaker electrical subsystem and introduce additional parameters: parallel resistance R_2 and parallel inductance L_2 [8] as shown in **Fig. 8**.

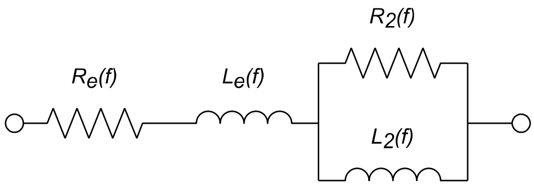


Fig. 8. Voice coil model using parameters R_2 and L_2

From the genetic algorithm point of view, these new model parameters will become new chromosomes of the individuals:

$$I = \left[L_e, Bl, R_{ms}, M_{ms}, R_2, L_2\right]. \tag{17}$$

Also, the fitness function will change slightly to take into account the new parameters:

$$E_1 = MSE_\omega \left[\frac{E(\omega)}{I(\omega)} - R_e - j\omega L_e - \frac{R_2 \cdot j\omega L_2}{R_2 + j\omega L_2} - \frac{Bl^2}{j\omega M_{ms} + \dfrac{K_{ms}}{j\omega} + R_{ms}} \right]. \tag{18}$$

These changes and complications of the model do not affect the convergence or speed of the genetic algorithm, but can significantly reduce the approximation error as shown in **Fig. 9**.

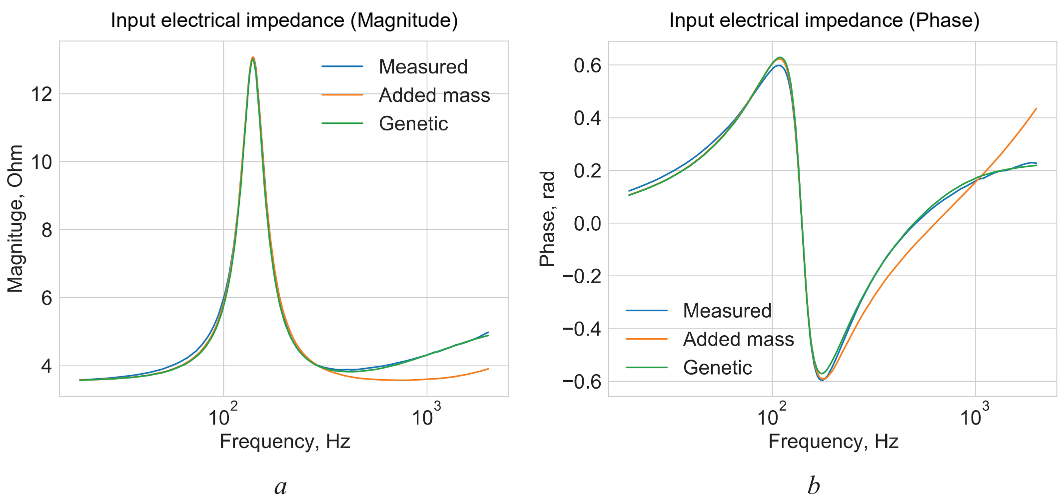


Fig. 9. Total input electrical impedance including *L*2 and *R*2 parameters: *a* – modulus; *b* – phase

As it can be seen in **Fig. 9**, more complicated model better corresponds to the measured response in the entire measured frequency range and is therefore more accurate. This example demonstrates the convenience of genetic algorithm usage when moving from identifying one model with specific parameters to another. The only things that should be changed in the entire algorithm are individual chromosomes that correspond to the model parameters and fitness function. In perspective, it is possible to identify more complex and accurate models (described in [8]) with more parameters without spending additional time for developing a specific identification methods. **Table 3** shows the comparison of the model parameters identified by the added mass method and using genetic algorithm after more complicated voice coil model was used.

Table 3

Comparison of identified model parameters (including R2 and L2)

Parameter	Added mass method	Genetic algorithm
f_{res}, Hz	137.2	138
R_e, Ohm	3.54	3.54
L_e, H	1.39e-4	0.41e-4
Bl, T*m	2.43	2.43
M_{ms}, kg	2.7e-3	2.8e-3
K_{ms}, N/m	2.04e3	2.1e3
R_{ms}, kg/s	0.62	0.63
R_2, Ohm	–	1.65
L_2, H	–	2.24e-4

4. Discussion

This paper described the full process of genetic algorithm adaptation and implementation for loudspeaker model identification. As it can be seen in the **Fig.7** and in the **Table 2** the model parameters (shown in the **Fig. 4**) identified using genetic algorithm and the added mass method (described in [5]) are very close to each other. This demonstrates that presented loudspeaker identification scheme using genetic algorithm is capable of finding correct model parameters.

Despite, the added mass method is commonly applied on practice, genetic algorithm application gives researchers a lot more flexibility for quick adaptation and model identification. This flexibility is demonstrated when more complicated voice-coil model (**Fig. 8**) was used. The algorithm adaptation for the new model identification is done in just few steps (equations (17), (18)) and much better model performance was achieved (**Fig. 9**).

On practice, presented scheme can be only directly applied to electrodynamic transducer model identification. However, it can be extended to identify models of other types of electroacoustic transducers used in the industry, such as piezoelectric hydrophones, for example.

In perspective, the versatility of genetic algorithm application allows to create a universal loudspeaker identification framework where most of the models can be identified using genetic algorithm, without spending time on developing a specialized identification procedure. The further research will be aimed on the development of such framework including various linear and also nonlinear models.

5. Conclusions

This paper presents the ready to use scheme for model identification of an electrodynamic transducer using genetic algorithm. Several conclusions that should be noted: the proposed fitness function is appropriate because the algorithm converges very quickly and finds the optimal values after a few generations. This proves that genetic algorithms can be successfully applied to identify models of electrodynamic and other types of acoustic transducers. However, the Re parameter, which is the voice-coil DC resistance, should be excluded from the optimization, as it can be measured directly by an ohmmeter. Also, for the other types of acoustic transducers, it is possible to assume that parameters that can be measured directly and without much effort should be excluded from the optimization.

Another important conclusion is that moving mass M_{ms} and suspension stiffness K_{ms} cannot be unambiguously determined with simultaneous optimization because they compensate each other (at least when using the presented fitness function). To solve this problem, it was proposed to exclude the K_{ms} parameter from the optimization and determine it using moving mass M_{ms} and resonance frequency (equation 15).

Also, the possibility of rapid adaptation of the genetic algorithm to more complex models with larger number of identified parameters without any loss of performance and convergence was shown. This demonstrates the genetic algorithm versatility and possibility of its use for more complex model identification that are difficult to identify with classical methods, including models with partial derivatives [9] and nonlinear models [10].

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