Application of Biologically Inspired Algorithms for Determining the Coefficients of Empirical Models for Determining Sound Absorption

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The paper investigates the possibility of applying biologically inspired algorithms for determining the optimal values of the coefficients in known empirical models for acoustic impedance. To solve this problem, a gray wolf algorithm was used, for cases of infinite and deterministic search space. Using the gray wolf algorithm, new values of the coefficients in the empirical model for the impedance of foam materials were determined. The new model provides satisfactory predictions of the sound absorption coefficient of open-cell polyurethane foams, compared to the experimental results obtained in an impedance tube. Known empirical models for impedance in which the constants are determined by the method of linear regression, give slightly better predictions of the coefficient of sound absorption of polyurethane foams compared to the new model in which the constants are determined using the gray wolf algorithm. The presented method of determining the coefficients of empirical models for impedance provides a basis for the application of other biologically oriented algorithms, as well as for their hybridization.

Keywords: Gray wolf algorithm, Empirical models for impedance, Sound absorption coefficient, Polyurethane foams

1. INTRODUCTION

Noise can affect human health, directly to the sense of hearing, but also to other organs, causing various symptoms and diseases. Due to the rapid industrialization and the fact that the standard of living in modern times is based on mechanization that directly affects noise pollution, noise is a hazard to human health. In order to improve the quality of life and protect the working and living environment, especially in densely populated areas, protection from noise and the strrugle against its harmful effects is one of the main solutions.

The application of absorption materials is very useful in noise control, because they reduce noise by expanding the wavefront of sound energy and converting it into heat. Absorption materials are characterized by a sound absorption coefficient that defines the ability of a material to absorb and transform part of the energy of sound into another form of energy [1]. The sound absorption coefficient of porous materials depends on several parameters, and some of them are: sound frequency, porosity of the material, thickness of the material layer, resistance to air flow. The absorption coefficient is a useful concept when using geometrical acoustic theory, especially to evaluate the decline and growth of sound energy in a room [2]. When sound is consider as a wave, it is necessary to use the concept of acoustic impedance. The values of the absorption coefficient are usually in range from 0-1.

Empirical acoustic models in combination with measurement results are used to determine the dependence of absorption coefficients as a function of frequency and material thickness. To determine the coefficients in the empirical model for impedance, numerical methods can be used, such as the method of least squares or methods of statistical data processing, respectively regression analysis.

In this paper, the application of a biologically inspired algorithm is presented, namely the gray wolf algorithm for determining the coefficients in the empirical model for acoustic impedance. The model for determining the characteristic acoustic impedance was performed on the basis of known dependences defined by Delany and Bazley [3]. The regression constants in this empirical model were determined in a new way, using a biologically inspired gray wolf algorithm. The accuracy of the new model was determined by comparing the predicted and experimental values for one type of polyurethane foam with open cells.

2. EMPIRICAL MODELS FOR DETERMINATION OF CHARACTERISTIC ACOUSTIC IMPEDANCE

Empirical models are commonly used to evaluate the acoustic properties of porous materials. Empirical models are used to estimate acoustic properties, namely complex propagation constants and characteristic impedances, using physical parameters or material properties.

The best known and one of the first empirical model is a Delany-Bazley model [4], for the determination of the acoustic impedance and the propagation coefficient of the fibrous absorption material. In this model, air flow resistivity is used as the only input parameter. The model is based on on numerous impedance tube measurements and is good for determining the group of acoustic properties at frequencies higher than 250 Hz, but not at low frequencies [5].

Qunli [6] later verified the Delany-Bazley model, using a large amount of experimental data for plastic foams, which cover a wider range of longitudinal airflow resistance values. Following the Delany-Bazley model Dunn & Davern [7] calculated new values of regression constants for polyurethane foams.

Voronina [8] model is a simple model based on the porosity of the material. This model uses the average pore diameter, frequency and porosity of the material to define the acoustic characteristics of the material.

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Empirical models are very useful because they use only one input parameter, flow resistivity, which is easily measurable. However, they are only suitable for one type of material and the certain frequency ranges.

2.1. MODEL FOR CHARACTERISTIC ACOUSTIC IMPENDANCE

In this paper, in order to prove the validity of the application of a biologically inspired algorithm to determine the characteristic acoustic impedance, the model defined by Delany-Bazley was used [3].

The dependencies in this model are given in the equations (1) – (4), [9].

$$Z_{CR} = \rho_0 c_0 \left[1 + C_1 \left(\frac{\sigma}{\rho_0 f} \right)^{C_2} \right] \tag{1}$$

$$Z_{CI} = -\rho_0 c_0 \left[C_3 \left(\frac{\sigma}{\rho_0 f} \right)^{C_4} \right] \tag{2}$$

$$\alpha = \left(\frac{2\pi f}{c_0} \right) \left[C_5 \left(\frac{\sigma}{\rho_0 f} \right)^{C_6} \right] \tag{3}$$

$$\beta = \left(\frac{2\pi f}{c_0} \right) \left[1 + C_7 \left(\frac{\sigma}{\rho_0 f} \right)^{C_8} \right] \tag{4}$$

Where are:

- Z_{CR} and Z_{CI} – real and imaginary part of characteristic acoustic impedance, Z_C,
- α and β – real and imaginary parts of the propagation constant, Γ,
- σ – airflow resistivity,
- f – frequency,
- ρ_0 – air density and
- c_0 – sound speed in air.

The sound absorption coefficient at normal incidence, α_n, for a firmly supported layer of material of thickness *d*, can be obtained using well - know expressions (5) and (6), with knowledge of the characteristic acoustic impedance and propagation constants Γ.

$$ZS = Z_C \coth \Gamma d \tag{5}$$

$$\alpha_n = 1 - \left| \frac{Z_S - \rho_0 c_0}{Z_S + \rho_0 c_0} \right|^2 \tag{6}$$

The values of the sound absorption coefficient, which will be used to check the proposed algorithm, are given in the Table 1 [4]. These values were obtained by measuring in an impedance tube by using the transfer function method between two microphones, described in the SRPS EN ISO 10534-2 standard [10]. This method is based on the decomposition of a standing wave which is formed in a tube by recording signals from two microphones and calculating their transfer function. The reflection coefficient is calculated from the transfer function and then the absorption coefficient is calculated. This method results in obtaining the value of the absorption coefficient at normal incidence, in the frequency range defined by the physical dimensions of the tube and the distance between the microphones.

3. MODEL

Since the middle of the XX, and especially with the beginning of the XXI century, methods have appeared that effectively solve complex optimization problems. The main characteristic of these methods is that they are inspired by phenomena in nature. For that reason, they are called biologically inspired methods. Among the best known, most popular, methods are: genetic algorithms (Genetic Algorithm - GA, John Holland, 1962), differential evolution (Differential Evolution - DE, R. Storn and K. Price 1996), particle swarm optimization (Particle Swarm Optmization - PSO, J. Kennedy and R. Eberhart in 1995), ant colony optimization (ACO M. Dorigo in the late 1990s), cuckoo search (CS – Xin-She Yang and Suash Deb, 2007), firefly algorithm (FA - Xin-She Yang, 2008), bat algorithm (Bat Algorithm – BA - Xin-She Yang, 2010), krill herd hlgorithm – (KHA – Amir H Gandomi and Amir H Alavi, 2012), gray wolf algorithm (Gray Wolf Optimizer, Seyedali Mirjalili, Seyed Mohammad Mirjalili, Andrew Lewis, 2014).

Table 1: Absorption coefficient values for foam HR 3744 [4]

	Material thickness (cm)									
f_c (Hz)	1	2	3	4	5	6	7	8	9	10
125	0.078945	0.052273	0.078038	0.091768	0.095615	0.099378	0.14166	0.14739	0.1988	0.23425
160	0.07159	0.064579	0.088787	0.095501	0.1163	0.13339	0.17142	0.1915	0.23306	0.28444
200	0.067147	0.071539	0.095544	0.1082	0.13866	0.16303	0.21552	0.26369	0.29383	0.36679
250	0.062784	0.081199	0.10469	0.12844	0.16959	0.20025	0.26771	0.3203	0.37254	0.47083
315	0.060061	0.082818	0.11674	0.15397	0.20809	0.24824	0.34862	0.41372	0.44536	0.56428
400	0.061533	0.088451	0.13883	0.19781	0.26972	0.31781	0.44411	0.49926	0.59604	0.73095
500	0.062915	0.10462	0.17202	0.25435	0.324	0.38727	0.55493	0.66397	0.75279	0.88024
630	0.07125	0.12535	0.22696	0.3171	0.44179	0.52143	0.74253	0.82768	0.8864	0.96609
800	0.086209	0.15796	0.29957	0.44704	0.59085	0.67178	0.88578	0.93204	0.94498	0.9434
1000	0.089769	0.19083	0.40787	0.5967	0.74673	0.80233	0.92326	0.92662	0.90819	0.8601
1250	0.1146	0.24294	0.56195	0.75699	0.84916	0.8587	0.86797	0.85938	0.83806	0.82517
1600	0.073466	0.30496	0.74481	0.86448	0.85371	0.84389	0.77397	0.80167	0.80959	0.90507
α_w	0.05	0.15	0.25	0.3(M)	0.35(M)	0.4(M)	0.55(M)	0.6(M)	0.65	0.75
f_c (Hz)	α_p									
250	0.063331	0.078519	0.105658	0.130203	0.172113	0.20384	0.277283	0.33257	0.370577	0.4673
500	0.065233	0.10614	0.17927	0.25642	0.34517	0.408837	0.580523	0.663637	0.745077	0.859093
1000	0.096859	0.197243	0.42313	0.600243	0.728913	0.777603	0.892337	0.906013	0.897077	0.876223

The advantage of these algorithms is that they can be applied to a large number of optimization problems, as well as their adaptability to the optimization problem. Also, these methods do not require experience in determining the initial values of variables, because it is possible to set a wide range for the initial values of variables. It is important to note here that the function optimized by these methods does not have to be differentiable and continuous, and that there is no limit to the number of variables to be optimized. However, perhaps the most important advantage of these methods is that they are all algorithmically designed and, as such, can be improved by simple modifications, thus achieving greater efficiency in finding the optimal solution.

3.1. GREY WOLF ALGORITHM

The Gray Wolf algorithm (The Gray Wolf Optimizer - GWO) was proposed by [11] Seyedali Mirjalili, Seyed Mohammad Mirjalil, Andrew Lewis and is based on the behavior of gray wolves during the search, pursuit of prey and the hunt itself. Gray wolves are social animals, living in packs, respecting a strict, social, hierarchy. The pack leaders are the dominant male (alpha male) and the dominant female (alpha female), which are called by the one name alpha, α. Alphas make the most important decisions for the pack. The second in the hierarchy of gray wolves are the so-called beta, β. The beta individual assists the alpha in organizing the pack when making decisions. Beta can be either male or female and they are the best candidates to inherit alpha. The lowest in the pack hierarchy are omegas, w and they are subordinate to everyone in the pack. There are also so-called deltas in the pack, δ, which carry out the orders of alpha and beta, and are superior to omegas. This category includes sentinels, hunters and caretakers.

In addition to the characteristics of social organization and strict hierarchy in the pack, another very important characteristic of gray wolves is organized behavior during hunting. The main phases of gray wolf hunting [11] are:

- tracking and approaching,
- pursuing, encircling, and harassing the prey until it stops moving,
- attack.

Precisely these two mentioned characteristics of gray wolves, hierarchical organization and hunting technique are mathematically modeled in order to desing an optimization algorithm [11].

Considering the hierarchy of gray wolves, when optimizing, the best solution will be alpha (α), while the second and third best solution will be beta (β) or delta (δ). Candidates for other good solutions will, of course, be omega (ω).

As mentioned above, grey wolves encircle prey during the hunt. The mathematical model of this behavior is given by equations (7) to (10), [11].

$$\vec{D} = \left|\vec{C}\cdot\overrightarrow{X_P}(t) - \vec{X}(t)\right| \tag{7}$$

$$\vec{X}(t+1) = \overrightarrow{X_P}(t) - \vec{A}\cdot\vec{D} \tag{8}$$

$$\vec{A} = 2\vec{a}\cdot\vec{r_1} - \vec{a} \tag{9}$$

$$\vec{C} = 2\cdot\vec{r_2} \tag{10}$$

Where are:

$\vec{D}$ – alpha position in the iterative process,

t – current iteration,

$\overrightarrow{X_P}$ – a vector indicates the position of the prey in the iteration *t*,

$\vec{X}$ – a vector indicates the position of the grey wolf in the iteration *t*,

$\vec{A},\vec{C}$ – coefficient vectors, which are calculated by equations (3) и (4),

$\vec{a}$ – vector of elements that are linearly decreased from 2 to 0 and

$\vec{r_1},\vec{r_2}$ –random vectors whose components take (random) values in the interval [0, 1].

The advantage of gray wolves, in hunting, is that they can recognize "easy" prey. As mentioned, the alpha is the one leading the hunt. The beta and delta might also participate in hunting. It is innate for wolves to find prey, but the very application of possible solutions to the search for space is difficult because, usually, the position of the optimal or best solution is not known. Therefore, in the proposed algorithm [11], it is assumed that alpha, beta and delta have better knowledge about the potential location of prey - their positions give the best solution. For this reason, the first three best solutions (alpha; $\overrightarrow{D_\alpha}$, beta; $\overrightarrow{D_\beta}$ and delta; $\overrightarrow{D_\delta}$ search agents) obtained, in an iterative process, oblige the other search agents (including the omegas) to update their positions according to them, Figure 1, [11]. This process in the algorithm is defined by equations (11), (12) and (13).

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}\cdot\overrightarrow{X_\alpha} - \vec{X}\right|,\ \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}\cdot\overrightarrow{X_\beta} - \vec{X}\right|,\ \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}\cdot\overrightarrow{X_\delta} - \vec{X}\right| \tag{11}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}\cdot\left(\overrightarrow{D_\alpha}\right),\ \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}\cdot\left(\overrightarrow{D_\beta}\right),\ \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}\cdot\left(\overrightarrow{D_\delta}\right) \tag{12}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \tag{13}$$

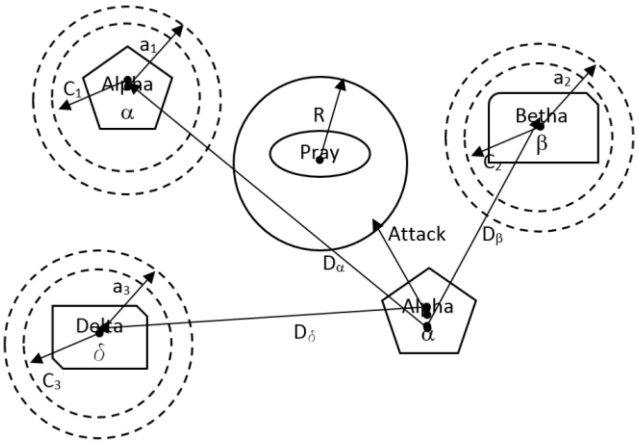

Figure 1: Illustration of updating search agent positions in the GWO algorithm

Respecting the proposed mathematical models, which mimic a pack of gray wolves in hunting, the following approximations were made, [11], in order to form a theoretical algorithm for gray wolves:

- Pack hierarchy assists GWO to save the best solutions obtained during iterative process
- The prey encirclement mechanism, defines a circle-shaped neighborhood around the solutions which can extend to a larger radius as a hyper-sphere.
- The random parameters ***A*** and ***C*** assist other candidates, varying the radius of the hypersphere, in finding the best solutions.
- The proposed hunting method allows candidate to locate the probable position of the prey.
- Exploration and exploitation are guaranteed by the adaptive values of ***a*** and ***A***.
- The adaptive values of parameters ***a*** and ***A*** allow GWO algorithm a smooth transition between exploration and exploitation.
- With decreasing ***A***, one half of the iterations refers to exploration, and the other half are dedicated to exploitation.

- The GWO has only two main parameters that need to be adjusted (***a*** and ***C***).

Based on all given mathematical models and the stated approximations, the proposed GWO algorithm is given in the form of pseudo code in A -1, [11].

A.1 Pseudo code of the gray wolf algorithm GWO

```
begin
    Objective function f(X), X = (x1, x2, ..., xd)^T
    Initialization of the gray wolf population, Xi (i = 1,2,3,...,n)
    Initialization a, A, C
    The calculation of the objective function for each of the agents search
    Xα The best search agent
    Xβ The second ranked agent search
    Xδ The third ranked search agent
    while (t < Number of iterations)
        for For each search agent
            Update positions for each agent
        end for
        Update a, A i C
        The calculation of the objective function for each agent search
        Update Xα, Xβ, Xδ
        t = t + 1
    end while
    Processing and displaying results
end
```

4. 5. RESULTS AND DISCUSSION

The application of optimization algorithms, ie algorithms that seek the best solutions, implies setting certain boundaries of the search space, Figure 2. These boundaries, in fact, represent the boundary conditions that must be met during the iterative process of searching the space for a possible solution.

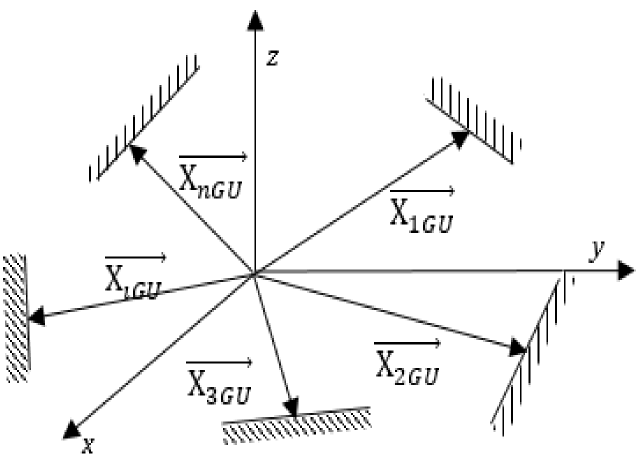

Figure 2: Search space constrained by boundary conditions ($\overrightarrow{X_{iGU}}$) for each of the variables whose values are sought

In the case of determining the sound absorption coefficient equation for a particular type of material, the objective function should calculate the coefficients, $C_1 \ldots C_8$ from equation (6), which will give the closest results to the results obtained by measurement, [4], given in Table 1: T(i), (8).

$$\Delta = \alpha_n(i) - T(i) \rightarrow 0 \qquad (14)$$

The only limitation in this problem is that the value α_n must be in the range from 0 to 1, [2], (9).

$$0 < \alpha_n \leq 1 \qquad (15)$$

The values of the coefficients can have values from $-\infty$ to $+\infty$, that is: $-\infty \leq C_i \leq +\infty$, i=1,…,8. In other words, in this problem, it is not possible, explicitly, to define the boundaries within which to look for coefficients, that is, the search space is infinite, Figure 3.

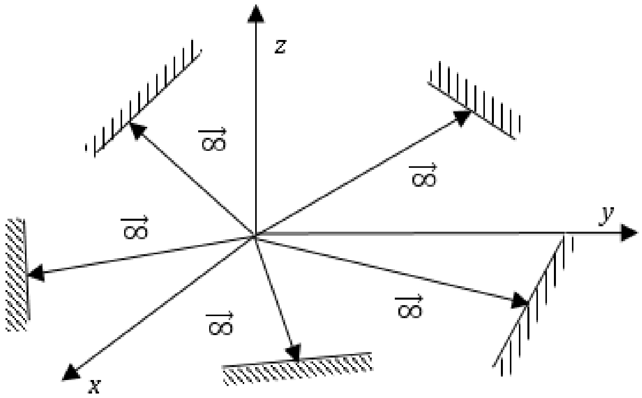

Figure 3: Infinite search space

No matter how experienced the researcher is in defining boundary value problems, it cannot avoid entering the space of the local minimum. This danger may lead the researcher to come up with a “best” solution at some point, when in fact a local minimum has been found.

In the GWO algorithm, which was applied in this case, the following algorithm parameters were applied:

- Number of search agents: 50
- The maximum number of iterations 1000, t=1,..,1000

The algorithm is implemented in the MatLab software package.

The application of the GWO algorithm went in two directions:

P1. Defining fixed search boundaries

The boundaries are set in the form of:

a) l =[$-\infty$ $-\infty$ $-\infty$ $-\infty$ $-\infty$ $-\infty$ $-\infty$ $-\infty$]; – lower boundaries values
h = [∞ ∞ ∞ ∞ ∞ ∞ ∞ ∞];– upper boundaries values

b) l = [$-l_1$ $-l_2$ $-l_3$ $-l_4$ $-l_5$ $-l_6$ $-l_7$ $-l_8$]; – lower boundaries values
h = [h_1 h_2 h_3 h_4 h_5 h_6 h_7 h_8]; – upper boundaries values

where – l_i и h_i are random chosen values

P2. Reducing the scope of the limits search

In this case, a certain modification of the original algorithm was performed by modifying the search space for possible solutions based on the variables that gave the best solution, equations (10) and (11).

$$l(i) = THeBestPos(i)*(-1) - r_z; \qquad (16)$$

$$h(i) = THeBestPos(i) + r_z; \qquad (17)$$

where r_z – a random number that is randomly selected depending on the best solution given in the vector *TheBestPos*.

The following paper provides comparative results for different search space boundaries.

4.1. Infinite search space P1.a

In the case of infinite search space (P1.a), the results were obtained, shown below, and illustrated in Figure 4 and Table 2, respectively:

```
Search time = 704.1551 sec
```

```
C1 = 3.4172;  C2 = -0.7412;
C3 = 0.77532; C4 = 0.6189;
C5 = 0.25774; C6 = 3124.0577;
C7 = 14.4902; C8 = 0.92315;
Best value: 6.0679
Mean value: 6.1925
Worst value: 54.4117
SD: 1.8996 – standard deviation
```

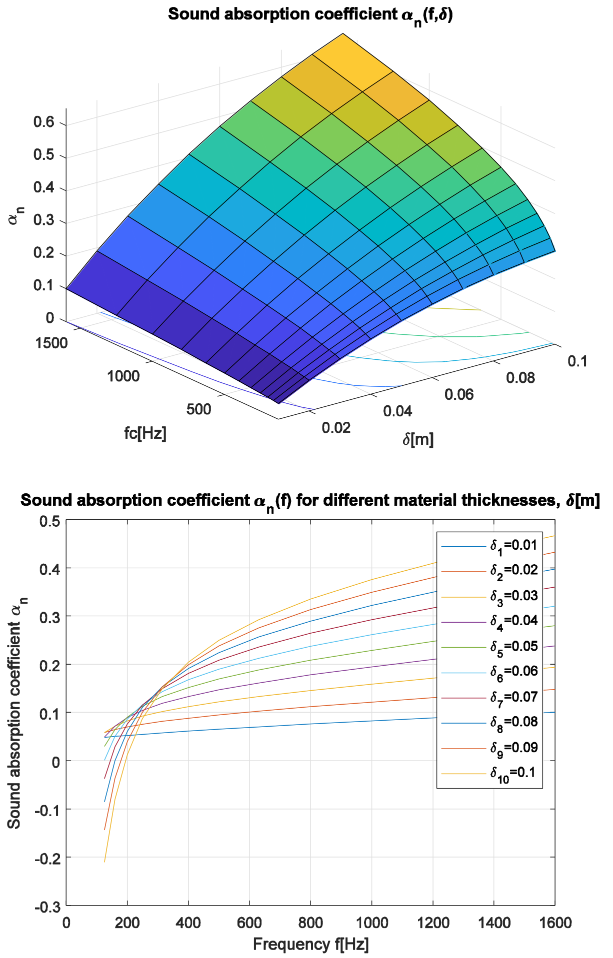

Figure 4: Graphical representation of the sound absorption coefficient $\alpha_n=F(f,\delta)$, at infinite search space

Table 2: Obtained values of α_n, for at infinite search space

	Material thickness δ[cm]									
f_C[Hz]	1	2	3	4	5	6	7	8	9	10
125	0.0485	0.0933	0.1337	0.1693	0.1998	0.2254	0.2464	0.2631	0.2761	0.2859
160	0.0504	0.0973	0.1401	0.1785	0.2123	0.2415	0.2665	0.2873	0.3045	0.3183
200	0.0525	0.1014	0.1465	0.1873	0.2239	0.2562	0.2845	0.3088	0.3296	0.3470
250	0.0549	0.1062	0.1536	0.1969	0.2362	0.2715	0.3028	0.3304	0.3545	0.3754
315	0.0578	0.1119	0.1619	0.2080	0.2501	0.2882	0.3226	0.3533	0.3807	0.4048
400	0.0614	0.1187	0.1719	0.2209	0.2659	0.3070	0.3443	0.3781	0.4085	0.4358
500	0.0654	0.1263	0.1826	0.2347	0.2825	0.3264	0.3664	0.4028	0.4358	0.4657
630	0.0702	0.1353	0.1955	0.2510	0.3019	0.3487	0.3914	0.4304	0.4660	0.4983
800	0.0762	0.1464	0.2110	0.2703	0.3247	0.3746	0.4201	0.4617	0.4996	0.5340
1000	0.0827	0.1584	0.2277	0.2911	0.3489	0.4017	0.4498	0.4937	0.5335	0.5697
1250	0.0903	0.1724	0.2469	0.3147	0.3762	0.4320	0.4827	0.5286	0.5701	0.6077
1600	0.1002	0.1904	0.2715	0.3446	0.4104	0.4695	0.5228	0.5707	0.6138	0.6525

From Table T-2, it can be seen that each value of α_n, in the range from 0 to 1. However, the error is quite large, Δ = **6.0679**, as is the search time (704.1551 sec).

4.2. Randomly selected search space, P1.b.

Obtained results for arbitrarily selected search space:: l_i = -20; h_i = 20, i = 1,..., 8, which are illustrated in Figure 5 and shown in Table 3, are:

```
Search time = 611.1237 sec
C1 = 1.0154;  C2 = -0.0039128;
C3 = 0.89559; C4 = -0.040922 ;
C5 = 0.54164; C6 = 0.19802;
C7 = 0.15113; C8 = 0.3144;
Best value: 0.1043
Mean value: 0.47815
Worst value: 30.5376
SD: 2.153
```

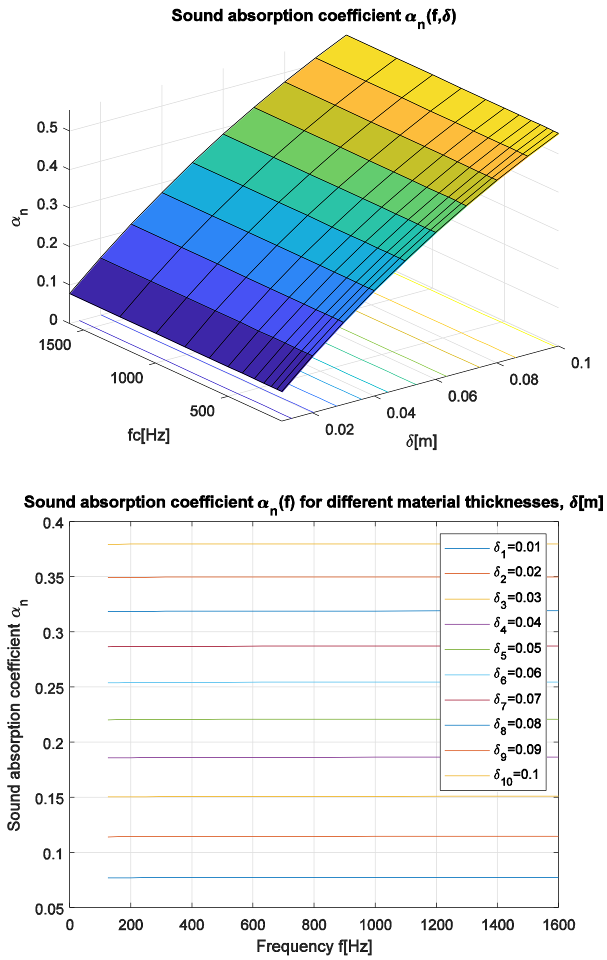

Figure 5: Graphical representation of the sound absorption coefficient $\alpha_n=F(f,\delta)$, in a determined search space

Table 3: Obtained values of α_n, for determined search space

	Material thickness δ[cm]									
f_C[Hz]	1	2	3	4	5	6	7	8	9	10
125	0.0769	0.1480	0.2136	0.2743	0.3304	0.3822	0.4302	0.4745	0.5156	0.5535
160	0.0770	0.1481	0.2137	0.2744	0.3305	0.3823	0.4303	0.4747	0.5157	0.5536
200	0.0770	0.1481	0.2138	0.2745	0.3306	0.3825	0.4304	0.4748	0.5158	0.5538
250	0.0770	0.1482	0.2139	0.2746	0.3307	0.3826	0.4305	0.4749	0.5159	0.5539
315	0.0771	0.1482	0.2140	0.2747	0.3308	0.3827	0.4307	0.4750	0.5161	0.5540
400	0.0771	0.1483	0.2141	0.2748	0.3309	0.3828	0.4308	0.4752	0.5162	0.5541
500	0.0771	0.1484	0.2141	0.2749	0.3310	0.3829	0.4309	0.4753	0.5163	0.5542
630	0.0772	0.1484	0.2142	0.2750	0.3312	0.3831	0.4311	0.4754	0.5164	0.5544
800	0.0772	0.1485	0.2143	0.2751	0.3313	0.3832	0.4312	0.4755	0.5166	0.5545
1000	0.0772	0.1485	0.2144	0.2752	0.3314	0.3833	0.4313	0.4757	0.5167	0.5546
1250	0.0773	0.1486	0.2145	0.2753	0.3315	0.3834	0.4314	0.4758	0.5168	0.5547
1600	0.0773	0.1487	0.2146	0.2754	0.3316	0.3836	0.4316	0.4759	0.5169	0.5540

As in the previous example, each value of α_n is in the range from 0 to 1, Table 3. Error, Δ = **0.1043**; is significantly less than the error obtained in infinite search space, and the search time is shorter (611.1237 sec).

4.3. Reducing the scope of the limits search P2

In the case of an infinite search space, and when it narrows in each iteration, equations (10) and (11), in relation to the values of the obtained variables, which at that time give the best solution, the results illustrated in Figure 6 and Table 4 are obtained:

```
Search time = 628.5198sec
C1 = 0.44309; C2 = 0.00512;
C3 = 0.15295; C4 = -0.02567;
C5 = 0.22699; C6 = 0.23031;
C7 = 0.30494; C8 =  0.26245;
Best value: 0.0862138277
Mean value: 0.6912305913
Worst value: 30.5388861113
SD: 2.4624322978
```

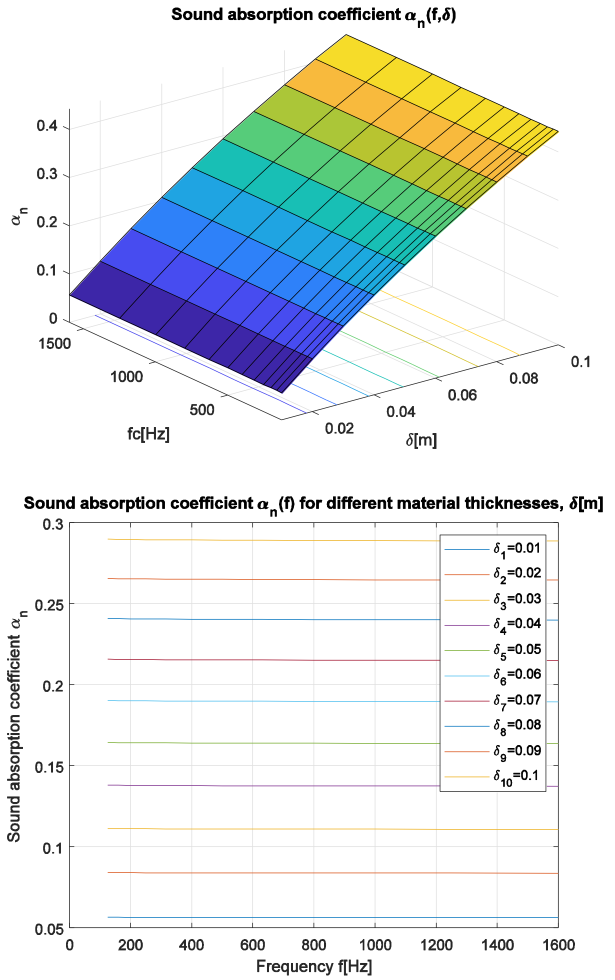

Figure 6: Graphical representation of the sound absorption coefficient αn=F(f,δ), when narrowing the search space

Table 4 shows that there is any value of α_n in the range from 0 to 1. This can get even less error than in the previous case: Δ = **0.0862138277**. Search time: 628.5198sec, is approximately the same.

Figure 7 shows the course of the iterative process in determining the coefficients $C_i, i = 1,\ldots,8$. From the diagram it can be seen that the convergence is very good, because already after some 30 steps comes to approaching the best values.

Table 4: Obtained values of α_n, in infinite search space, but in narrowing search space

	Material thicknesses δ[cm]									
f_C[Hz]	1	2	3	4	5	6	7	8	9	10
125	0.0564	0.1096	0.1599	0.2074	0.2523	0.2947	0.3348	0.3728	0.4087	0.4426
160	0.0564	0.1096	0.1599	0.2073	0.2522	0.2946	0.3347	0.3726	0.4085	0.4425
200	0.0564	0.1096	0.1598	0.2073	0.2521	0.2945	0.3346	0.3725	0.4084	0.4424
250	0.0563	0.1095	0.1598	0.2072	0.2520	0.2944	0.3345	0.3724	0.4083	0.4422
315	0.0563	0.1095	0.1597	0.2071	0.2520	0.2943	0.3344	0.3723	0.4082	0.4421
400	0.0563	0.1094	0.1596	0.2071	0.2519	0.2943	0.3343	0.3722	0.4081	0.4420
500	0.0563	0.1094	0.1596	0.2070	0.2518	0.2942	0.3342	0.3721	0.4080	0.4419
630	0.0563	0.1094	0.1595	0.2069	0.2517	0.2941	0.3341	0.3720	0.4078	0.4418
800	0.0562	0.1093	0.1595	0.2069	0.2516	0.2940	0.3340	0.3719	0.4077	0.4416
1000	0.0562	0.1093	0.1594	0.2068	0.2516	0.2939	0.3339	0.3718	0.4076	0.4415
1250	0.0562	0.1093	0.1594	0.2067	0.2515	0.2938	0.3338	0.3717	0.4075	0.4414
1600	0.0562	0.1092	0.1593	0.2067	0.2514	0.2937	0.3337	0.3716	0.4074	0.4413

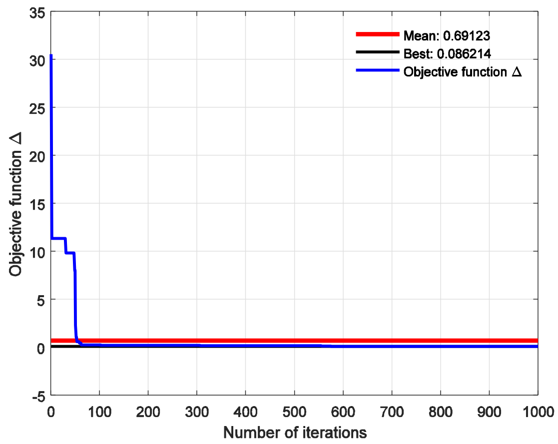

Figure 7: The course of the iterative process in determining the coefficients C_i, $i = 1, \ldots, 8$, by narrowing the search space

The result obtained by this procedure is slightly worse than the results obtained using the empirical Dunn-Davern model, which is known in the literature as the most commonly used model for foam materials, and especially for polyurethane foams, for which it was formed. Using the Dunn-Davern model, absolute error values of 4.7% and relative error of 14.21% were obtained [9] in relation to the experimental values of the sound absorption coefficient for polyurethane foam (HR 3744).

This indicates the fact that it is necessary to investigate modifications of the proposed algorithm or a combination with other biological algorithms - hybridization, in order to obtain better solutions.

Table 5: Coefficients in empirical models

Model	Coefficients							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Dunn-Davern [7]	0.114	0.369	0.0985	0.758	0.168	0.715	0.136	0.491
GWO	0.44309	0.00512	0.15295	-0.02567	0.22699	0.23031	0.30494	0.26245

This indicates that it is necessary to investigate modifications of the proposed algorithm or a combination with other biological algorithms - hybridization, in order to obtain better solutions.

5. CONCLUSION

The paper presents the possibility of using biologically inspired algorithms for determining the coefficients in empirical models for acoustic impedance, which are usually determined using regression analysis and the least squares method. The gray wolf algorithm was applied for cases of infinite and determined search space. As with other biologically inspired algorithms, local minimum spaces need to be avoided. Using a modifications, the infinite space is corrected and narrowed, whereby an optimal solution is obtained with good convergence of results. The results of the research showed that biologically inspired algorithms are a suitable tool for determining constants in empirical models for determining acoustic impedance. A further direction of research in order to increase the accuracy of empirical models for impedance whose coefficients are determined using biologically inspired algorithms is to hybridize the gray wolf algorithm with some other biologically inspired algorithms.

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