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The application of artificial intelligence in the optimal design of mechanical systems

A Poteralski and M Szczepanik

Institute of Computational and Mechanical Engineering, Faculty of Mechanical Engineering, Silesian University of Technology

Email: arkadiusz.poteralski@polsl.pl

Abstract. The paper is devoted to new computational techniques in mechanical optimization where one tries to study, model, analyze and optimize very complex phenomena, for which more precise scientific tools of the past were incapable of giving low cost and complete solution. Soft computing methods differ from conventional (hard) computing in that, unlike hard computing, they are tolerant of imprecision, uncertainty, partial truth and approximation. The paper deals with an application of the bio-inspired methods, like the evolutionary algorithms (EA), the artificial immune systems (AIS) and the particle swarm optimizers (PSO) to optimization problems. Structures considered in this work are analyzed by the finite element method (FEM), the boundary element method (BEM) and by the method of fundamental solutions (MFS). The bio-inspired methods are applied to optimize shape, topology and material properties of 2D, 3D and coupled 2D/3D structures, to optimize the termomechanical structures, to optimize parameters of composites structures modeled by the FEM, to optimize the elastic vibrating systems to identify the material constants for piezoelectric materials modeled by the BEM and to identify parameters in acoustics problem modeled by the MFS.

1. Introduction

In the present paper, the application of bio-inspired methods in optimization of several structures is presented [1][7]. The evolutionary algorithms (EA), the artificial immune systems (AIS) and the particle swarm optimizers (PSO) are used to optimize shape, topology and material properties of 2D [16] and 3D structure, to optimize of termomechanical structures, to optimize of composites structures, to optimize of elastic vibrating systems and to identify in acoustics problem. Structures considered in this work are analyzed by the finite element method (FEM), the boundary element method (BEM) and by the method of fundamental solutions (MFS).

2. Optimization methods

Soft computing techniques resemble human reasoning more closely than traditional techniques, which are largely based on conventional logical systems or rely heavily on the mathematical capabilities of a computer. These computing techniques are often used to complement each other in applications. It should be pointed out that simplicity and complexity of systems are relative, and certainly, most successful mathematical modeling of the past have also been challenging and very significant. Unlike hard computing schemes, which strive for exactness and for full truth, soft computing techniques exploit the given tolerance of imprecision, partial truth, and uncertainty for a particular problem.

Another common contrast comes from the observation that inductive reasoning plays a larger role in soft computing than in hard computing.

Three important areas of soft computing methods, namely:

- Evolutionary Computation (EC),
- Artificial Immune Systems (AIS),
- Particle Swarm Methods (PSM),

are presented in the paper.

2.1. Evolutionary Computation (EC)

Evolutionary algorithms [5] are algorithms searching the space of solutions and they are based on the analogy to the biological evolution of species. Like in biology, the term of an individual is used, and it represents a single solution. Evolutionary algorithms operate on populations of individuals, so while the algorithm works, all the time we deal with a set of problem solutions. An individual consists of chromosomes. Usually it is assumed that an individual has one chromosome. Chromosomes consist of genes which are equivalents of design variables in optimisation problems. The adaptation is computed using fitness function. All the genes of an individual decide about the fitness function value.

In the first step, an initial population of individuals is created. Usually, the values of the genes of particular individuals are randomly generated. In the next step, the fitness function value for each individuals is computed. Then, evolutionary operators change genes of the parent population individuals, they are then selected for the offspring population, which becomes a parent population and the algorithm is continuing iteratively till the end of the computation. The termination condition of the computation can be formulated as the maximum number of iterations.

In evolutionary algorithms the floating-point representation is applied, which means that genes included in chromosomes are floating-point numbers. Usually the variation of the gene value is limited.

Evolutionary operators change gene values like the biological mechanisms of mutation and crossover. Different kinds of operators are presented in publications, and the basic ones are:

- uniform mutation,
- mutation with Gaussian distribution,
- boundary mutation,
- simple crossover,
- arithmetical crossover.

An important element of an evolutionary algorithm is the mechanism of selection. The probability of the individual’s survival depends on the value of the fitness function. Ranking selection is performed in a few steps. First, the individuals are classified according to the value of the fitness function, then a rank value is attributed to each individual. It depends on the individual’s number and the rank function. The best individuals obtain the highest rank value, the worst obtain the lowest one. In the final step individuals for the offspring generation are drawn, but the probability of drawing particular individuals is closely related to their rank value.

2.2. Artificial Immune Systems (AIS)

The artificial immune systems (AIS) are developed on the basis of a mechanism discovered in biological immune systems [17]. An immune system is a complex system which contains distributed groups of specialized cells and organs. The main purpose of the immune system is to recognize and destroy pathogens - funguses, viruses, bacteria and improper functioning cells. The lymphocytes cells play a very important role in the immune system. The lymphocytes are divided into several groups of cells. There are two main groups B and T cells, both contains some subgroups (like B-T dependent or

B-T independent). The B cells contain antibodies, which could neutralize pathogens and are also used to recognize pathogens.
The artificial immune systems [3] take only a few elements from the biological immune systems. The most frequently used are the mutation of the B cells, proliferation, memory cells, and recognition by using the B and T cells. The artificial immune systems have been used to optimization problems in classification and also computer viruses recognition. The cloning algorithm presented by de Castro [3] uses some mechanisms similar to biological immune systems to global optimization problems. The unknown global optimum is the searched pathogen. The memory cells contain design variables and proliferate during the optimization process. The B cells created from memory cells undergo mutation. The B cells evaluate and better ones exchange memory cells. In Wierzchoń [17] version of Clonalg the crowding mechanism is used - the diverse between memory cells is forced. A new memory cell is randomly created and substitutes the old one, if two memory cells have similar design variables. The crowding mechanism allows finding not only the global optimum but also other local ones. The presented approach is based on the Wierzchoń [17] algorithm, but the mutation operator is changed. The Gaussian mutation is used instead of the nonuniform mutation in the presented approach.
In the first stage of a flowchart of an artificial immune system the memory cells are created randomly. They proliferate and mutate creating B cells. The number of nc clones created by each memory cell is determined by the memory cells objective function value. The objective functions for B cells are evaluated. The selection process exchanges some memory cells for better B cells. The selection is performed on the basis of the geometrical distance between each memory cell and B cells (measured by using design variables). The crowding mechanism removes similar memory cells. The similarity is also determined as the geometrical distance between memory cells. The process is iteratively repeated until the stop condition is fulfilled. The stop condition can be expressed as the maximum number of iterations [10].

2.3. Particle Swarm Methods (PSM)

The particle swarm algorithms [4][13], similarly to the evolutionary and immune algorithms, are developed on the basis of the mechanisms discovered in the nature. The swarm algorithms are based on the models of the animals social behaviours: moving and living in the groups. The animals relocate in the three-dimensional space in order to change their stay place, the feeding ground, to find the good place for reproduction or to evading predators. We can distinguish many species of the insects living in swarms, fishes swimming in the shoals, birds flying in flocks or animals living in herds.
A simulation of the bird flocking was published in [13]. They assumed that this kind of the coordinated motion is possible only when three basic rules are fulfilled: collision avoidance, velocity matching of the neighbours and flock centring. The computer implementation of these three rules showed very realistic flocking behaviour flying in the three dimensional space, splitting before obstacle and rejoining again after missing it. The similar observations concerned the fish shoals. Further observations and simulations of the birds and fishes behaviour gave in effect more accurate and more precise formulated conclusions [13]. The results of this biological examination where used by Kennedy and Eberhart [4], who proposed Particle Swarm Optimiser – PSO. This algorithm realizes directed motion of the particles in n-dimensional space to search for solution for n-variable optimisation problem. PSO works in an iterative way. The location of one individual (particle) is determined on the basis of its earlier experience and experience of whole group (swarm). Moreover, the ability to memorize and, in consequence, returning to the areas with convenient properties, known earlier, enables adaptation of the particles to the life environment. The optimisation process using PSO is based on finding the better and better locations in the search-space (in the natural environment that are for example hatching or feeding grounds).
The algorithm with continuous representation of design variables and constant constriction coefficient (constricted continuous PSO) has been used in presented research. In this approach each particle oscillates in the search space between its previous best position and the best position of its neighbours, with expectation to find new best locations on its trajectory. When the swarm is rather small (swarm

consists of several or tens particles) it can be assumed that all the particles stay in neighbourhood with currently considered one. In this case we can assume the global neighbourhood version and the best location found by swarm so far is taken into account – current position of the swarm leader.
At the beginning of the algorithm the particle swarm of assumed size is created randomly. Starting positions and velocities of the particles are created randomly. The objective function values are evaluated for each particle. In the next step the best positions of the particles are updated and the swarm leader is chosen. Then the particles velocities are modified and particles positions are also modified. The process is iteratively repeated until the stop condition is fulfilled. The stop condition is typically expressed as the maximum number of iterations.
The general effect is that each particle oscillates in the search space between its previous best position (position with the best fitness function value) and the best position of its best neighbour (relatively swarm leader), hopefully finding new best positions (solutions) on its trajectory, what in whole swarm sense leads to the optimal solution.

3. Overview of the scientific research

Three optimization algorithms described above were applied to the following tasks which are authors' research i.e.:

- optimization of shell and shell solid structures due to the shape, topology and material properties,
- optimization of termomechanical structures,
- identification and optimization of composites structures,
- optimization of elastic vibrating systems,
- identification in acoustics problem.

The first task concerns the optimization of shell and shell solid structures (figure 1a). At the beginning of optimization process the material is homogeneous. During this process material properties can be changed (density of material). Finally after optimization heterogeneous material is obtained [8]. As a result of changing of the material properties a part of the finite elements could be eliminated, resulting in a change of the outer boundary of shell or shell-solid structure (shape optimization) and were generated new internal boundaries as a holes (topology optimization). The optimization was performed using the artificial immune system, the particle swarm optimizer and the evolutionary algorithm. In the table 1 input data are presented i.e.: total load Q, constraint on maximal displacement u, thickness of 2D structure and range of changing of densities ρ_e.

Table 1. The input data to the optimization task of a shell-solid structure

shell thickness [mm]	u [mm]	Q [kN]	range of ρ_e [g/cm^3]
10.0	1.2	1.08	$0 \le \rho_e < 2.36$ elimination $2.36 \le \rho_e \le 7.86$ existence

Result after optimization process in the form of the map of displacements after deformation in the figure 1b is presented.
Examples of application the optimization of shell and solid structures due to the shape, topology and material properties has been published in several articles [2][12].

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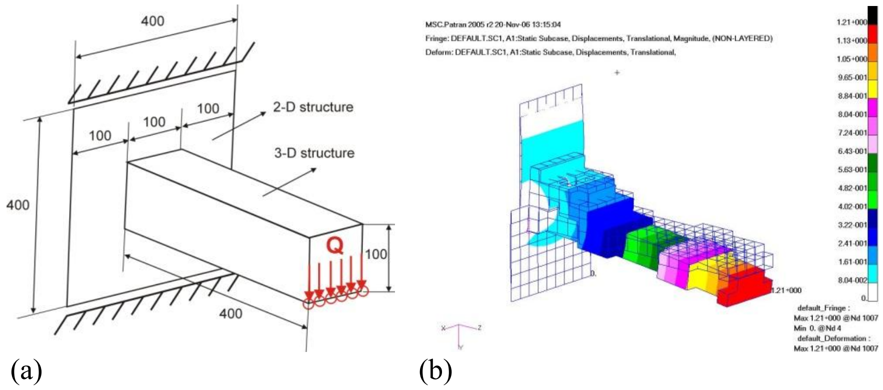

Figure 1. (a) Geometry and scheme of loading, (b) The map of displacements after deformation for optimal construction

The next task concerns the optimization of thermoelasticity problem (coupled field) [14]. Considered bodies were subjected to simultaneous impact of thermal and mechanical fields (figure 2a). The coupled fields are a special case of coexistence phenomena of different physical nature. For a coupled problems, a set of variables describing physical phenomenon data cannot be reduced and replaced by a description of a single physical phenomenon and the phenomenon occurring in specific areas they cannot be separated. For coupled fields there are two classes of problems: coupling occurs at the interface areas by boundary conditions (eg. interaction fluid - solid), areas where there are phenomena overlap partially or completely, so that coupling takes place by the equations describing different physical phenomena (eg. thermoelasticity, piezoelectricity, electromagnetism). As an optimization example of coupled structures, thermo-mechanical systems are considered, for which the optimum shape of radiators modelled using Bezier curve (figure 2b) for several objective function is searched (minimization of volume, temperature and the maximum value of equivalent stresses). The optimization was performed using the artificial immune system and the particle swarm optimizer. In the table 2 input data are presented i.e.: pressure, heat flux, ambient temperature and heat convection coefficient.

Table 2. Boundary conditions values

Pressure	5000Pa
Heat flux	1000W/m^2
Ambient temperature	25 °C
Heat convection coefficient	2W/m^{2}K

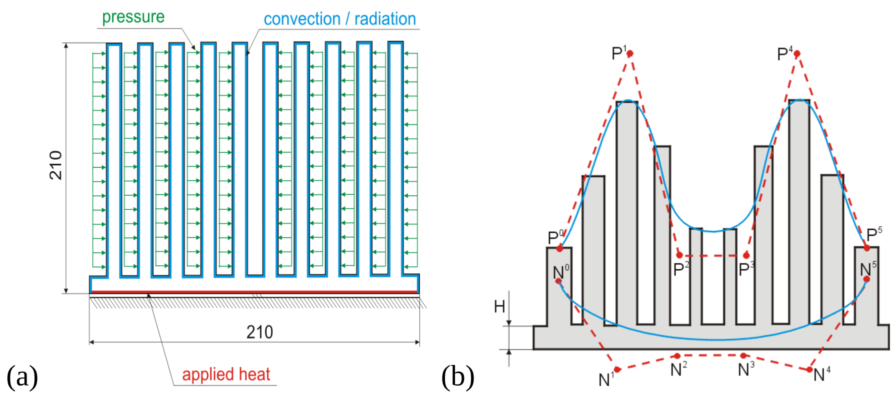

Figure 2. (a) Geometry and scheme of loading, (b) Design parameters

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Geometry after optimization process for three different optimization criteria in the figure 3 is presented.

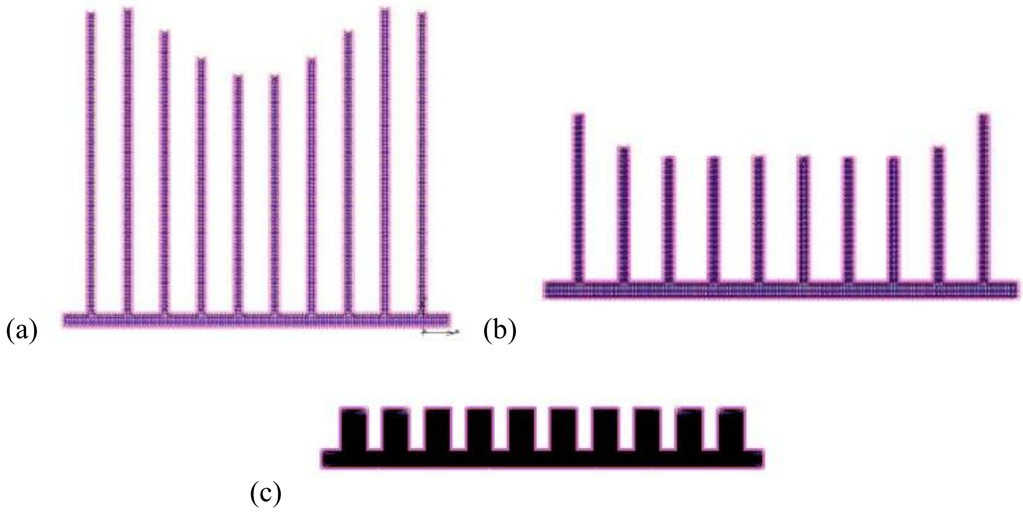


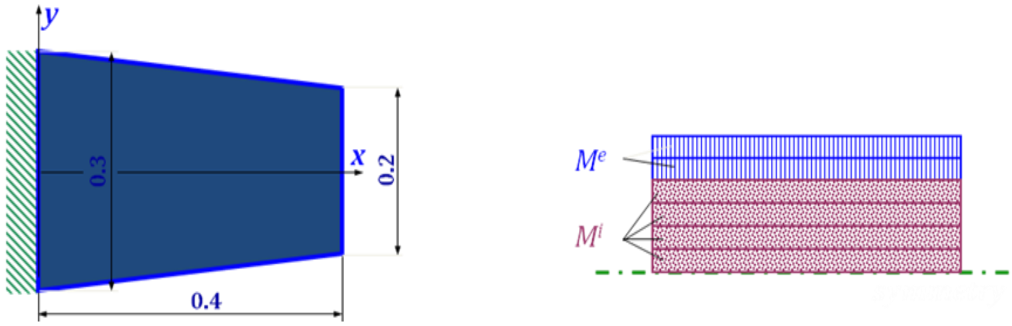
Figure 3. Geometry after optimization process: (a) minimization of temperature, (b) minimization of volume, (c) minimization of equivalent stresses

Examples of application the optimization of termomechanical structures has been published in the paper [14].

Another problem is the optimization and identification of certain parameters for composite systems, which have high strength-to-weight ratio compared with traditional materials. The laminates, being multilayered, fibre reinforced composites, have especially superior properties. Searched: the number and order of layers and arrangement of layers and their thickness allowing for optimal strength properties. Identification of elastic constants material in a multi-layer laminate of different sequences of layers were also performed. The optimization was performed using the artificial immune system and the particle swarm optimizer.
A symmetric hybrid laminate plate made of two materials is considered (figure 4b). The external plies of the laminate are made of material M_e, the core of the plate is made of the material M_i .
The properties of materials are:

- material M_e (graphite-epoxy, T300/5280): E_1=181GPa, E_2=10.3GPa, G_{12}=7.17GPa, ν_{12}=0.28, ρ=1600kg/m^3;
- material M_i (glass-epoxy, Scotchply 1002): E_1=38.6GPa, E_2=8.27GPa, G_{12}=4.14GPa, ν_{12}=0.26, ρ=1800 kg/m^3.

where: E_1 – axial Young's modulus, E_2 - transverse Young's modulus, G_{12} - axial-transverse shear modulus, ν_{12} - axial-transverse Poisson ratio.



(a) (b)

Figure 4. The hybrid laminate plate: (a) dimensions and bearing; (b) location of materials (for 12-plies case)

The aim of the optimization is to find the optimum ply angles of the hybrid laminate for the given number and thicknesses of the laminas (stacking sequence of plies). It is assumed that the number of laminas made of particular materials is constant. Results in the form of ply angles of the hybrid laminate for four variants in the table 3 are presented.
The AIS and PSO are employed to solve the optimization problem.

Table 3. Optimization results

Variant	Plies no.	Stacking sequence (ply angles)	max($\lvert\omega_{cl}-\omega_{ex}\rvert$) [Hz]
continuous	12	(-48.3/-49.9/50.3/50.2/50/50.4)s	64.864
	24	(49.1/-48.9/48.9/49.1/49.2/49.4/49.2/-49.2/49.2/49.2/49.1/-48)s	65.718
5^o	12	(50/-50/-50/-50/-55/-55)s	64.633
	24	(-50/50/50/-50/-50/50/50/-50/-50/-50/50/-45)s	65.613
15^o	12	(45/-45/-60/-60/-60/-60)s	63.02
	24	(45/45/45/-45/45/-60/75/-60/60/-75/75/-60)s	63.750
45^o	12	(45/-45/-45/-90/-90/-90)s	60.663
	24	(-45/45/45/-45/-45/-90/45/45/45/-90/-90/45)s	63.525

Examples of application the identification of certain parameters for composite structures has been published in paper [9].

Next problem is devoted to reinforced structures considered in this work are dynamically loaded and analyzed by the coupled boundary and finite element method (BEM/FEM).
The task of analysis was based on the determination of the fields of displacements, accelerations and the boundary forces (stresses) in shell structures, reinforced with stiffeners dynamically loaded and optimization of the structural form of these structures for the optimization criteria, built on designated fields. The optimal positions of stiffeners are searched in order to maximize stiffness of the plate subjected to the sinusoidal load, the Heaviside load and for three kinds of supports. The optimization was performed using the artificial immune system and the particle swarm optimizer.
The optimization of the reinforced rectangular plate shown in figure 5 is presented. The plate is dynamically loaded and different kinds of load and support are considered (figure 6).

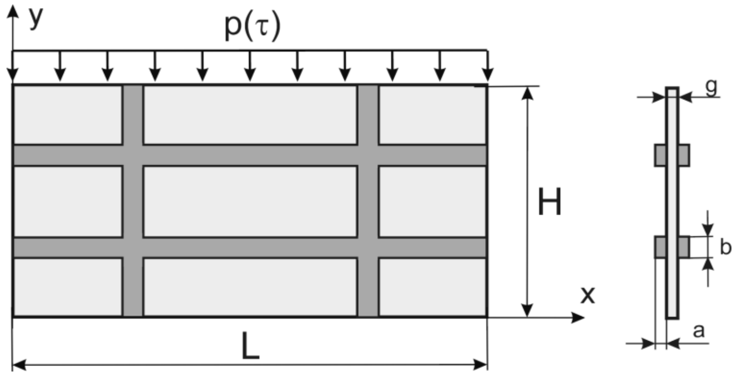
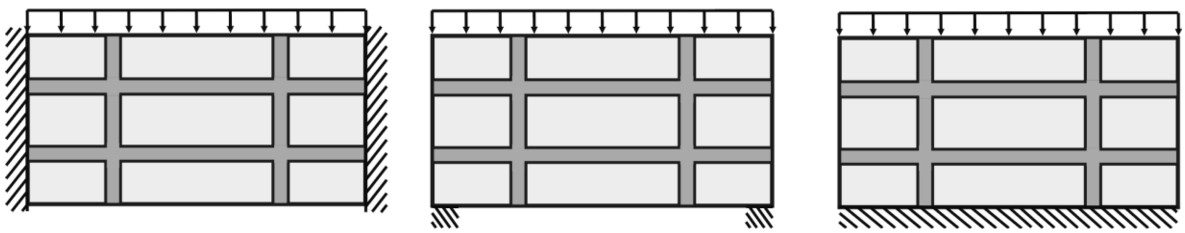


Figure 5. Reinforced rectangular plate

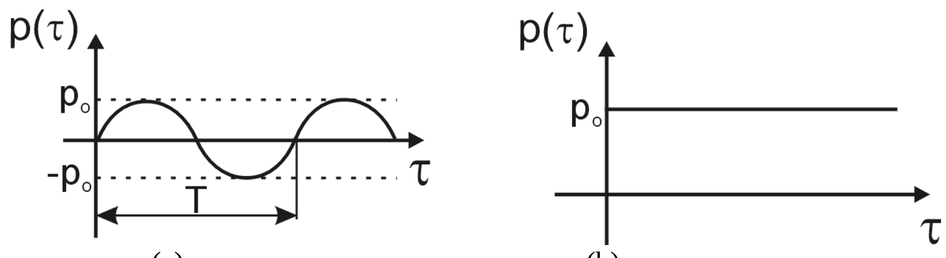
Three different supports are considered: a) support A – the plate is fixed on the left and right edge, b) support B – the plate is fixed on two supports, each of 0.5 cm long, c) support C – the plate is supported on the bottom.



(a) (b) (c)

Figure 6. Types of supports: (a) support A, (b) support B, (c) support C.

The plate is reinforced by the frame structure composed of 4 straight beams of square cross-section (2a×b). The length and the height of the plate is L=10 cm and H=5 cm, respectively. The thickness of the plate is g=0.25 cm, the dimensions of cross-section of beams are 2a=0.5 cm and b=0.5 cm.
The material of the plate in plane stress and the frame is aluminum, for which the values of mechanical properties are: modulus of elasticity E=70 GPa, Poisson's ratio ν=0.34 and density ρ=2700 kg/m3. The material is homogeneous, isotropic and linear elastic.
The uniformly distributed load is applied at the upper edge of the plate. Two kinds of time dependent loads are considered (figure 7): a) the sinusoidal load $p(\tau)=p_o\sin(2\pi\tau/T)$ with the period of time T=20π μs, and b) the Heaviside load $p(\tau)=p_oH(\tau)$. The amplitude of the load in both cases is p_o=10 MPa.



(a) (b)

Figure 7. Dynamic loadings: (a) sinusoidal, (b) Heaviside

Results after optimization problem in the table 4 are presented.

Table 4. Values of design variables, J and R

Load	Support	Design variables [cm]				J_o [10^{-4}cm]	J [10^{-4}cm]	R [%]
		X1	X2	Y1	Y2			
AIS								
Sinus.	A	4.75	2.86	0.88	2.75	89	76	15
	B	4.75	1.81	0.57	2.75	92	73	21
	C	1.20	1.82	0.50	2.75	82	62	24
Heav.	A	0.50	4.75	0.50	4.50	112	91	19
	B	4.75	1.41	0.50	4.50	211	149	29
	C	0.50	2.20	1.70	2.80	49	42	14
PSO								
Sinus.	A	4.75	2.86	0.88	2.75	89	76	15
	B	4.75	1.81	0.57	2.75	92	73	21
	C	1.20	1.82	0.50	2.75	82	62	24
Heav.	A	0.50	4.75	0.50	4.50	112	91	19
	B	4.75	1.41	0.50	4.50	211	149	29
	C	0.50	2.20	1.70	2.80	49	42	14

More information of the optimization of dynamically loaded reinforced structures in paper [11] is presented.

The last problem, which uses a bio-inspired algorithms is identification of complex values of the impedances of room walls for the acoustic problem. The acoustic field control and design require the determination of structure parameters, e.g. the acoustic absorption of building materials. The pressure measurements are simulated by the method of fundamental solutions MFS (meshless method). The optimization was performed using the artificial immune system and the particle swarm optimizer.
Complex values of the impedances $Z_1 \div Z_4$ of room walls are identified. The geometry and other parameters of the analysed 2-D model of a room are presented in Figure 8. The same structure was considered by Dutilleux et al. The dimensions of the room model are: a = 3.4 m and b = 2.5 m. The acoustic medium is air at the temperature 20°C. The analysis is performed for the frequency equal to 100 Hz. Eight sensors are located at points with coordinates related to the wave length λ and the room dimensions. The number of both the boundary points and the sources is equal to 54. The sources are located at a circle of radius r = 2.5 m, centered at the geometric centre of the rectangle (Figure 8).
The AIS and its hybrid version HAIS [6], EA and PSO are employed to solve the optimization problem (table 5).

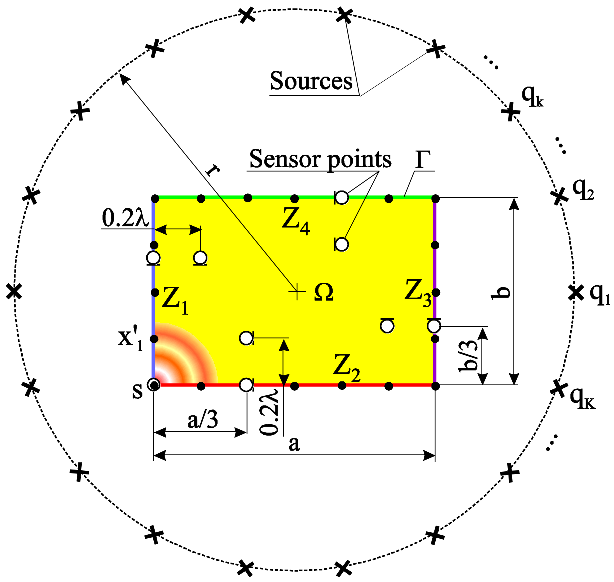


Figure 8. Scheme of the problem solved by the MFS and the HAIS

Table 5. Reference values of genes and results obtained by using different methods

Results	Reference values	(8,56)-ES, Dutilleux et al.	AIS, EA, PSO	HAIS
p_1	4920	4706	4833	4920
p_2	1590	1591	1484	1590
p_3	2390	2487	2362	2390
p_4	3720	3756	3678	3720
p_5	3400	3400	3370	3400
p_6	50	84	49	50
p_7	3500	3568	3720	3500
p_8	2200	2174	2256	2200

Examples of application identification in acoustics problem has been published in several articles [6][15].

4. Conclusions

In the paper the formulation and application of the finite element method, boundary element method, method of fundamental solutions and the bio-inspired methods to optimization of several structures is presented. The bio-inspired methods can be simply implemented because it needs only the values of objective functions. The important feature of this approaches is the strong probability of finding the global optimal solutions. The described approaches are free from limitations connected with classic gradient optimization methods.

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