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USING OPTIMIZATION ALGORITHMS TO DESIGN PHONONIC BARRIERS PROTECTING MONUMENTS OR BUILDING FACADES

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Abstract

The work compares the design of phononic structures using two types of optimization algorithms. Using the genetic algorithm and the simulated annealing algorithm, optimal layer distributions were obtained in which the phononic band gap phenomenon occurs. The mechanical wave propagating in the obtained structure, for the given frequency ranges, significantly reduces the transmitted energy, thanks to which the building facade or monument located behind the obtained barrier is exposed to much smaller vibrations, which significantly reduces damage related to long-term fatigue load. The mechanical wave propagation was modeled using the Transfer Matrix Method algorithm and the proprietary objective function allows for the reduction of wave transmission with the simultaneous reduction of high transmission peaks with small half-widths.

Keywords: *Transfer Matrix Method; Genetic algorithm; Simulated annealing; Acoustic filtering; Phononic Structures*

Introduction

Most monuments and historic buildings are located in urban areas. The increasing population density of cities and, consequently, the development of transport and industry increase the intensity of mechanical waves in the environment. A large number of private cars or cars used to transport goods generate mechanical waves from the engines and contact of the tires with the ground. Similarly, processes in the production of goods increase the energy of waves in the environment. The propagating mechanical wave exerts a time-varying pressure on nearby objects. The facades of buildings of particular historical importance or works of art are exposed to constant vibrations of the medium. This may cause erosion resulting from long-term exposure to fatigue loads, or cause the phenomenon of parametric resonance in objects with complex geometry, which may ultimately lead to the destruction of elements of a given work of art. Moreover, the pressure acting on a large surface of the building may cause vibrations to propagate throughout the structure and translate into vibrations of objects attached to the building walls.

One of the solutions that allows to limit the impact of vibration energy on the facades of historical buildings or works of art is the use of appropriate mechanical wave filters. Particularly interesting are modern phononic structures in which the phononic band gap (PhnBG) phenomenon occurs [1-3]. The mechanical wave inside the quasi-one-dimensional filter structure is reflected at the boundaries of the layers and, as a result of destructive interference, frequency ranges (bandgaps) are created for which the mechanical wave does not propagate in the structure.

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In addition to acoustic barriers [4] and filters [5] of the phononic structure, they are also used as selective filters [6], waveguides [7], sensors [8], concealment acoustic [9], medical devices [10], mechanical wave lenses [11, 12], acoustic diodes [13] or energy harvesters [14-16].

Many centers conduct research on the properties and applications of phononic structures. Much of the work related to phononic crystals focuses on topology optimization [17-22]. In the works [23-26] optimization algorithms were used to minimize the transmission of mechanical waves. Work was also carried out on maximizing the reflection coefficient for the largest possible range of mechanical wave energies. The influence of layer thickness in phononic structures made of, among others, amorphous materials on the transmission of mechanical waves was also investigated [27, 28]. The occurrence of numerically obtained band gaps has been experimentally demonstrated [29].

Phononic structures are characterized by high dispersion and bandgaps show a greater reduction in wave energy for a large number of layers of the structure, which leads to the formation of high intensity peaks and low half-width in the spectrum. As the number of layers increases, the number of possible material distributions in the structure increases exponentially. The high level of complexity of the problem of designing phononic mechanical wave filters leads to the use of heuristic optimization algorithms.

Phononic structures are optimized in terms of modifying the bandgap width or structure topology [30-33]. Another example of the use of optimization algorithms may be to simultaneously increase the safety and usability of a structure while minimizing its production costs [34, 35]. Multi-criteria optimization algorithms allow the determination of the most optimal solutions even in contradictory conditions [36], although it is always some kind of compromise resulting from the minimization of the objective function [37, 38]. Optimization algorithms allow searching the solution space regardless of the class of the problem being considered and are successfully used to optimize issues such as composite structures [39], design of high-rise buildings [40] or adjacent buildings [41], or to find optimal locations for shock absorbers in construction system [42].

Many different types of optimization algorithms are described in the literature. Classical optimization algorithms include the quasi-Newtonian BFGS [43-45], in which the Hessian matrix is not determined analytically on the basis of the second partial derivatives of the objective function but is approximated using finite differences gradient approximations for the determined objective function, which is a generalization the numerical secant method, except that the multidimensional case is considered. Another type of optimization algorithm belonging to the group of Evolutionary Strategies (ES) algorithms is the CMA-ES algorithm (Covariance Matrix Adaptation-Evolution Strategy) [46, 47]. This algorithm uses a multivariate normal distribution of potential solutions and then modifies it in subsequent iterations until the optimal solution is reached. These algorithms are most often used when information about the gradient is not possible to obtain, the difference quotients of the function do not provide reliable information, the objective function is multimodal, noisy or there are discontinuities in it.

When creating optimization algorithms, the natural environment is often an inspiration. Such solutions include, among others, the Gray Wolf Optimizer (GWO) algorithm [48] and the Black Widow Optimization (BWO) algorithm [49]. The Gray Wolf meta-heuristic algorithm implements the hierarchy and behavior of the wolf pack during hunting, translating it into a search in the space of solutions to the optimization problem. Another meta-heuristic algorithm based on natural evolution is the Black Widow algorithm. The subsequent phases include initialization, selection, crossbreeding, mutation and the phase of cannibalism of the least adapted individuals.

The next group of optimization algorithms are Neighborhood search algorithms. These types of algorithms most often use a multiple start search mechanism to generate “better” and “different starting points” to explore potential improvements or unexplored areas using local exploration procedures [50]. The most commonly used algorithms of this class include the Variable Neighborhood Search algorithm [51], Greedy Randomized Adaptive Search Procedure (GRASP) [52], Scatter Search [53] and Tabu Search [54].

Another group are algorithms inspired by physical processes related to music, metallurgy or even complex dynamic processes such as avalanches [50]. A combination of global and local (neighborhood-based) search techniques are used in these stochastic optimization algorithms. The most commonly used are Harmony Search [55], Memetic Algorithm [56] and Simulated Annealing [57].

Swarm algorithms use decentralized processes of self-organizing systems, which may be natural or artificial [58, 59]. Due to the high effectiveness of these algorithms, they are even used in construction engineering [60]. The most popular ones include the Krill Herd algorithm [61].

Particle swarm optimization (PSO) [58], [62], Ant Colony Optimization (ACO) [63, 64], Whale optimization algorithm [65], Polar bear algorithm [66] and the Dragonfly algorithm [67].

Derivative-free optimization (DFO) algorithm belongs to a class of deterministic algorithms in which the solution is obtained by running the algorithm multiple times. It uses mathematical convergence analysis to ensure that the optimal point is reached [58, 68]. Another example of a deterministic algorithm is Mesh Adaptive Direct Search (MADS) [69], which performs adaptive search on meshes by controlling mesh refinement and each iteration generates a trial point on the mesh that refines the current best solution.

The last class of optimization algorithms discussed are evolutionary algorithms. Nature-inspired non-gradient population algorithms typically consist of four main steps: selection, recombination, reproduction and mutation. They also appear in versions used for multi-objective optimization (MOO), such as MOO using Genetic Algorithm (MOGA) [70], Non-dominated Sorting Genetic Algorithm-III (NSGA-III) [71], Strength Pareto Evolutionary Algorithm 2 (SPEA2) [72, p. 2], Pareto Archived Evolution Strategy (PAES) [73], Pareto Envelope-based Selection Algorithm (PESA) [74], Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D) [75], Multi-objective Vortex Search [76] and Multi-objective Artificial Algae Algorithm [76].

The most important algorithms from the family of evolutionary algorithms include the genetic algorithm. It is mainly used to optimize the topology of phononic structures to obtain the widest possible band gaps [77-79].

In this work, a genetic algorithm and a simulated annealing algorithm were used and compared to design mechanical wave filters to protect monuments and facades of historical buildings. The transmission of the mechanical wave spectrum was determined using the Transfer Matrix Method algorithm.

Algorithms used

Algorithm determining the transmission of a multilayer phononic structure

Using the Transfer Matrix Method (TMM) algorithm, the transmission T was determined from Eq. (1) for a quasi-one-dimensional phononic structure (Fig. 1).

$$T = \frac{Z_{out}}{Z_{in}} |\boldsymbol{M}_{11}|^{-2} \tag{1}$$

Z_{in} is the acoustic impedance of the medium from which the mechanical wave is incident and Z_{out} is the acoustic impedance of the medium to which the mechanical wave is transmitted. The acoustic impedance Z_i for layer i consists of the speed of the mechanical wave in the medium c_i and its density ϱ_i as $Z_i = c_i \varrho_i$.

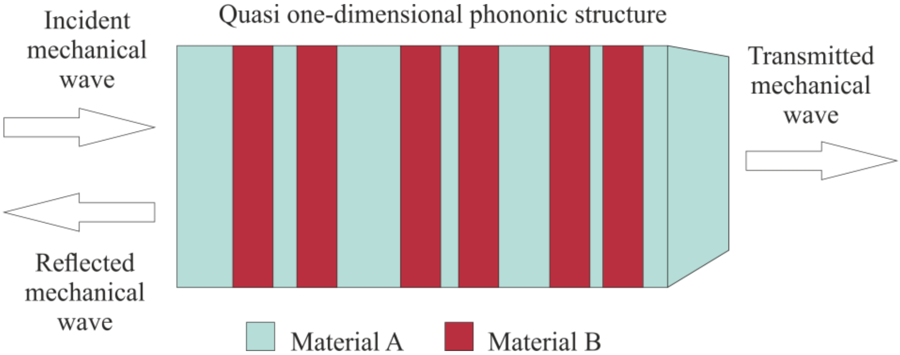

Fig. 1. Multilayer structure in the TMM algorithm

Transmission is the ratio of the transmitted wave to the incident wave and can be determined from the characteristic matrix $\boldsymbol{M}$ from Eq. (2).

$$\boldsymbol{M} = \Phi_{in,1}\left[\prod_{i=1}^{N-1} P_i \Phi_{i,i+1}\right] P_N \Phi_{N,out}\ . \tag{2}$$

Where the transmission matrix $\Phi_{i,i+1}$ for the boundary of layers i and $i+1$ is defined as

$$\Phi_{i,i+1} = \begin{bmatrix} \frac{1}{t_{i,i+1}} & \frac{r_{i,i+1}}{t_{i,i+1}} \\ \frac{r_{i,i+1}}{t_{i,i+1}} & \frac{1}{t_{i,i+1}} \end{bmatrix}, \tag{3}$$

where the Fresnel coefficients transmission $t_{i,i+1}$ and reflectance $r_{i,i+1}$ are defined as

$$t_{i,i+1} = \frac{2Z_{i+1}}{Z_{i+1}+Z_i}\ , \tag{4}$$

$$r_{i,i+1} = \frac{Z_{i+1}-Z_i}{Z_{i+1}+Z_i}\ . \tag{5}$$

The propagation matrix P_i, inside a given layer i with a thickness d_i is defined by

$$P_i = \begin{bmatrix} \exp\left(j\frac{2\pi f}{c_i}d_i\right) & 0 \\ 0 & \exp\left(-j\frac{2\pi f}{c_i}d_i\right) \end{bmatrix}, \tag{6}$$

where f is a frequency.

Genetic algorithm (GA)

One of the most frequently used optimization algorithms is the genetic algorithm presented in [80]. Fig. 2 shows a diagram of the genetic algorithm used in this work.

In the first step, the genetic algorithm and the Transfer Matrix Method are initialized. The first population of structures with a random distribution of materials is created. In the next step, the transmission distribution for each structure is determined. Then the structures are sorted by minimizing the objective function F_C defined as

$$F_C = \left\| \int_{f_{min}}^{f_{max}} T(f) df \right\| \cdot \left\| \int_{f_{min}}^{f_{max}} \left| \frac{\partial T(f)}{\partial f} \right| df \right\| , \tag{7}$$

The first normalized integral is responsible for minimizing transmission in the frequency range from f_{min} to f_{max}. The second one is responsible for minimizing the occurrence of high-intensity peaks with small half-widths. Normalization affects the weight of the integral elements within a given population, but to compare structures between populations it should be omitted.

$$F'_C = \int_{f_{min}}^{f_{max}} T(f) df \cdot \int_{f_{min}}^{f_{max}} \left| \frac{\partial T(f)}{\partial f} \right| df , \tag{8}$$

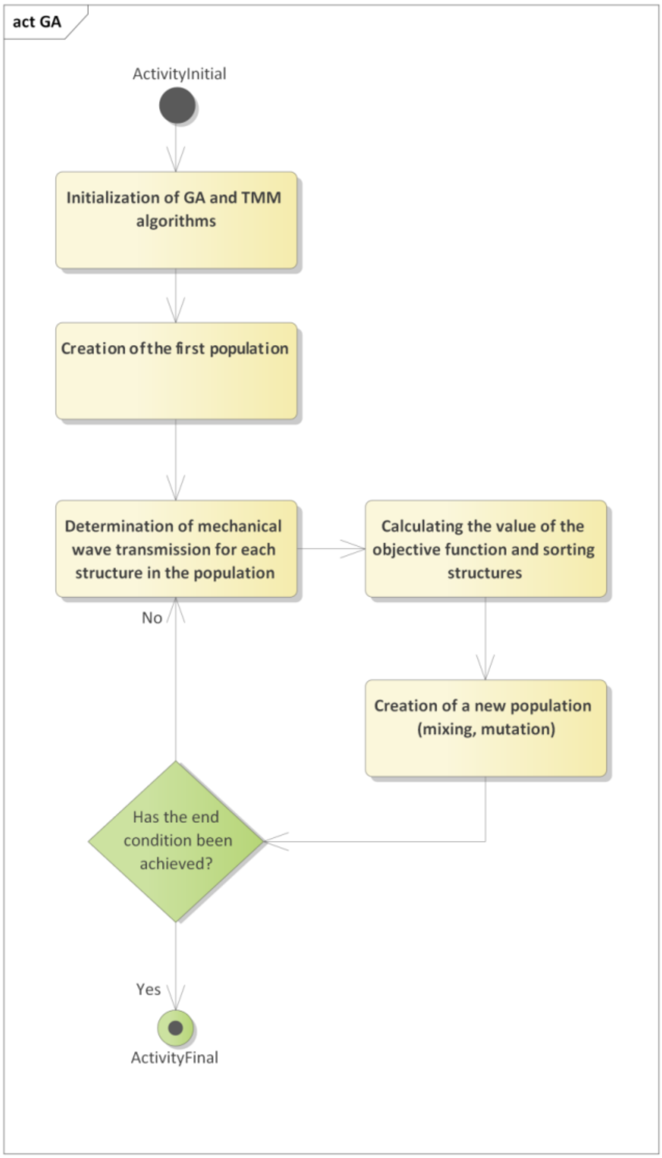

Fig. 2. Structure of the genetic algorithm used

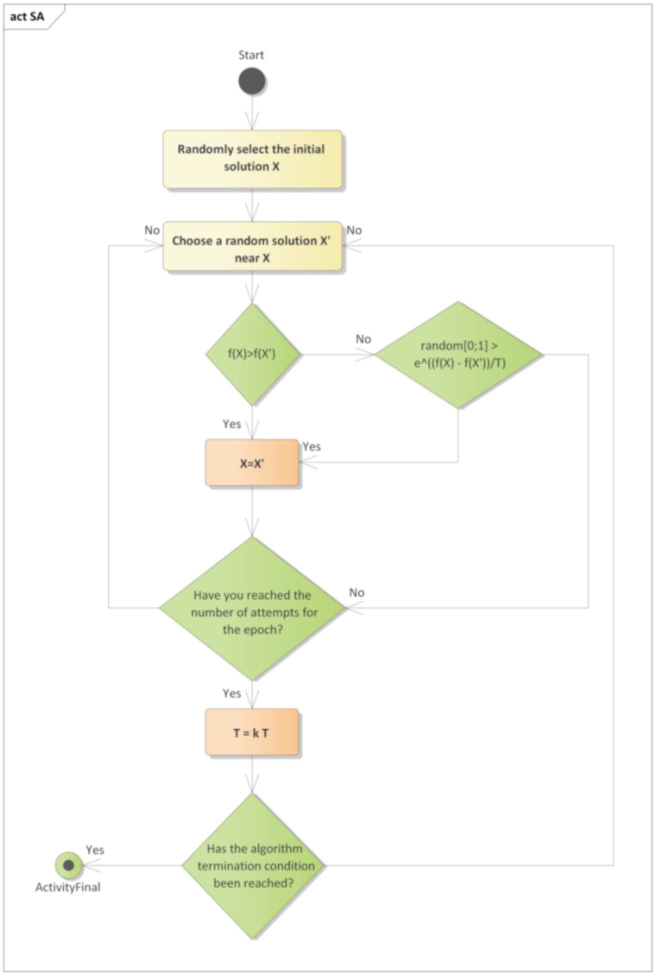

Fig. 3. Structure of the simulated annealing algorithm used

The two most favorable structures are left unchanged, the two least favorable are replaced with newly drawn structures and the remaining structures of the analyzed population are crossed according to the roulette wheel algorithm. Then, in order to minimize the chance of being in the local minimum of the solution space, each layer of all structures analyzed within a given population is subjected to a mutation process with a 1% chance of changing the material of a given layer. The full cycle of the genetic algorithm is repeated until the final condition is reached, which is assumed to be the achievement of a given number of algorithm repetitions.

Simulated Annealing (SA)

One of the most flexible techniques available for solving difficult optimization problems is Simulated Annealing (SA). This algorithm can be applied to large problems regardless of the differentiability, continuity and convexity conditions that are typically required in conventional optimization methods. As with other combinatorial techniques, solution encoding, definition of the neighborhood of a given configuration, objective function and transition mechanisms are critical to the success of practical simulated annealing implementations.

In the annealing process, the solid is exposed to high temperature followed by controlled cooling. As part of this process, it is possible to obtain high-quality crystals used in industry [81].

Based on the annealing process, a simulated annealing (SA) algorithm was created, which is used for combinatorial optimization, i.e. finding the most optimal solution (the state with the lowest 'energy') of a given problem. The main features of the annealing process are the state transition mechanism and the cooling schedule.

The first mention of the simulated annealing algorithm was in the early 1950s by Metropolis and it was intended to model the crystallization process. However, the use of the algorithm to solve optimization problems was carried out only in the 1980s by independent research by *S. Kirkpatrick et al.* [82] and *V. Černý* [83]. The optimal solution is an analogy of a perfect crystal, while a crystal with defects corresponds to a local optimal solution [84]. Temperature in the simulated annealing algorithm is a control parameter that must be properly specified.

Fig. 3 shows a diagram describing the operation of the SA algorithm. In the first step, any solution X from the problem domain is randomly selected. Then, the solution X' is determined near the solution X. The distance between the solutions X and X' in the problem space is related to the value of the T parameter in such a way that a higher value of the T parameter increases the space of searched solutions Then, the values of the objective function f are determined for the considered structures X and X'. If the value of the objective function of structure X' is more favorable than the value of the objective function of solution X, then solution X' is adopted as the new solution X. Otherwise, a value from the range [0;1] is drawn and if it is greater than the value of the function exp $((f(X) - f(X'))/T)$, the less favorable solution X' is still taken as X. Then a new solution X' is drawn for a given epoch (at a constant value of T). When all given solutions for a given epoch have been analyzed, the value of the T parameter is reduced by the k factor and a new epoch is analyzed. If the end condition is reached, the algorithm stops.

Results

The work sought the best distribution of materials for a fifty-layer composite phononic structure composed of glass (material A) and epoxy resin (material B). The materials were selected to be transparent and durable and at the same time differ significantly in the value of acoustic impedance, which affects the occurrence of the phononic band gap phenomenon. Table 1 shows the material parameters of the layers of the structures analyzed in this work. The external environment was air.

Both algorithms used the same objective function described by equation (7) and the study was carried out in the range of acoustic frequencies up to 20kHz.

Table 1. Material properties.

	Air	**Glass**	**Epoxy resin**
Symbol	E	A	B
Phase velocity [m/s]	343	4000	2535
Mass density [kg m^{-3}]	1.21	3880	1180

In the genetic algorithm, the number of structures in the population was 24. 200 iterations of the algorithm were performed. The chance of mutation was 2% of each layer in each population structure. The two best structures were transferred to the next population, 20 structures were mixed according to the roulette wheel algorithm, where the structures with the most favorable parameters had a greater chance of mixing. The two least favorable structures were completely replaced to reduce the chance of the algorithm getting stuck in the local minimum of the solution space. Using a genetic algorithm, 4,800 structures were analyzed with a total state space of $5.63 \cdot 10^{14}$ material distributions in the structure.

In the simulated annealing algorithm, the *k* coefficient was set to 0.8, which, with 50 layers, gives subsequent epochs with the number of changed layers {40, 32, 26, 20, 16, 13, 10, 8, 7, 5, 4, 3, 3} after 250 iterations per era. Using the simulated annealing algorithm, a total of 3251 structures were analyzed.

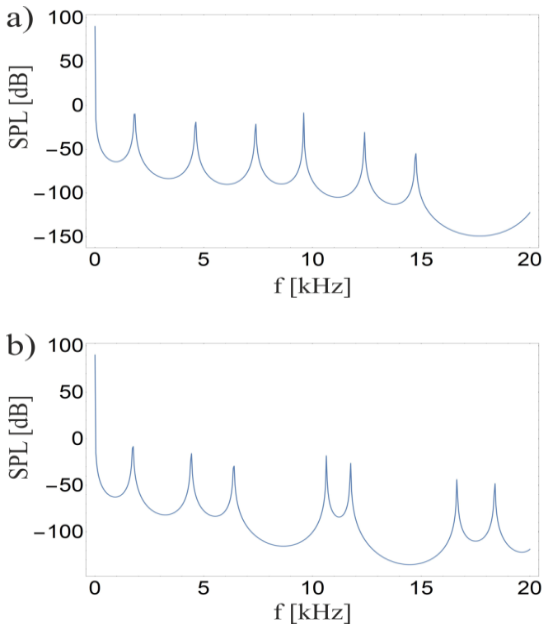

Fig. 4. Transmission for the best structures obtained using a) genetic algorithm and b) simulated annealing

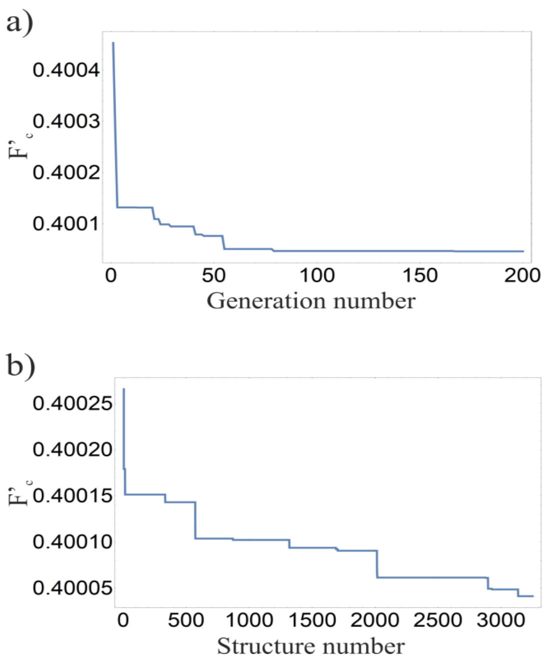

Fig. 5. Convergence of the objective function for a) genetic algorithm and b) simulated annealing

As part of searching the space of possible solutions, the genetic algorithm found the $A_8B_2ABA_4BA_4BAB_2AB_6AB_2A_5BA_9$ structure as the most favorable one, while the simulated annealing algorithm found the $A_{11}B_4AB_4AB_2AB_5A_6BAB_2A_4BA_6$ structure. The subscript determines the number of times a layer appears and therefore its thickness. The structure determined by the genetic algorithm consisted of 17 layers and the one determined by simulated annealing consisted of 15 layers, which means that the second structure may be cheaper to produce.

The mechanical wave transmission for the obtained structures is shown in figure 4. The transmission is shown for an acoustic wave source with a Sound Pressure Level (SPL) of 90 dB over the entire frequency range. As can be seen, the SPL level of the wave for both designated structures was below 0 dB, which results in a significant reduction in the energy of the mechanical wave.

Fig. 5 shows the convergence graphs of both algorithms. As can be seen in figure 5a, the genetic algorithm determined the optimal solution after 70 generations, i.e. after 1680 examined structures. However, the simulated annealing algorithm found the optimal layer distribution after analyzing 3140 structures. Both algorithms met the expected goals, but the genetic algorithm found the desired distribution at twice the speed.

Conclusions

As part of the work, two heuristic optimization algorithms were used to design a filter composed of a quasi-one-dimensional phononic structure. Using the genetic algorithm and the simulated annealing algorithm, distributions of materials in the phononic structure were obtained, for which the mechanical wave transmission was determined using the Transfer Matrix Method algorithm. Both obtained structures have very good transmission characteristics, significantly reducing the power of the mechanical wave, so they can be used as mechanical wave filters to protect the facades of historical buildings and works of art.

In summary, the simulated annealing algorithm determined a solution with a lower objective function value by searching a larger solution space, but in twice as many steps. From an engineering point of view, both structures have favorable transmission characteristics.

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