



# Comparing Optimized Sound Absorption Coefficient of Aluminum Foam with Local Search Algorithm, Genetic Algorithm, and Particle Swarm Optimization

Rohollah Fallah Madvari<sup>1</sup>, Mohsen Niknam Sharak<sup>2\*</sup>, Mohammad Javad Jafari<sup>3</sup>, Faezeh Abbasi Balochkhaneh<sup>3</sup>

<sup>1</sup>Industrial Diseases Research Center, Department of Occupational Health Engineering, School of Public Health, Shahid Sadoughi University of Medical Sciences, Yazd, Iran.

<sup>2</sup>PhD Graduate in Mechanical Engineering, University of Birjand, Birjand, Iran.

<sup>3</sup>Department of Occupational Health Engineering, School of Public Health and Safety, Shahid Beheshti University of Medical Sciences, Tehran, Iran.

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#### \*Corresponding Author:

Mohsen Niknam Sharak

#### Email:

mohsen.niknam@gmail.com

#### Tel:

+98 936 4342414

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## ABSTRACT

**Introduction:** The principle of passive sound control is based on the phenomenon of sound absorption by absorbers. The factors affecting sound absorption include porosity, pore size, pore opening size, thickness, and air flow resistance.

**Materials and Methods:** In this study, the authors compared the optimization results of the effective parameters on sound absorption coefficient (AC) using the three optimization methods: Guided Local Search (GLS), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The programming was done in MATLAB software. Thicknesses of 5, 10, 20, 30 and 40 mm were chosen for optimization at frequencies of 500 to 3000 Hz.

**Results:** In frequencies above 2 kHz (thickness 5 to 40 mm), the three optimal methods had the same performance and estimated AC of 1. At low frequencies of 2 kHz and thicknesses of 30 and 40 mm, GA and PSO methods obtained an AC of 1.

**Conclusion:** It seems that the GA and PSO optimization algorithm are suitable methods to optimize the AC of metal foam in low and high frequencies.

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## Introduction

One of the sound engineering and technical control methods is controlling based on absorption and insulation<sup>1</sup>. This control reduces the overall sound by increasing the surface absorption coefficient<sup>2</sup>. By absorbing sound and preventing its transmission, it leads to an increase in the comfort of people in the work environment. With the advancement of technology, obtaining

new materials can create a great effect in the wide and new industrial space, which can be mentioned as one of these materials, metal foam based on aluminum. One of the properties of this foam is sound absorption coefficient (AC) and its features include low density, high mechanical resistance, resistance to high heat and corrosion<sup>3</sup>. Among the factors affecting AC by aluminum foam, the authors can mention porosity, pore size, pore

opening size, thickness, air flow resistance, and pore morphology<sup>4</sup>. In a study by Shen et al., the results showed that metal foam has a good sound absorption capacity<sup>5</sup>. Whereas, the important point is to investigate the cellular structure of the foam and achieve the maximum state of the AC; in this direction, laboratory methods and optimization algorithms can be used.

But, it should be noted that the laboratory method is difficult and requires cost, time, and laboratory facilities. As a result, optimization algorithms can be a more suitable option. The purpose of optimization is to find the best acceptable solution, according to the constraints and needs of the problem<sup>6</sup>. Among the optimization algorithms, the meta-heuristic algorithm can be mentioned, which includes particle swarm optimization (PSO), genetic algorithm (GA), guided local search (GLS), differential evolution (DE), ant harmony search and etc<sup>7</sup>. Also, meta-heuristic algorithms are widely used in engineering optimization<sup>8</sup>. Local search algorithms move from one solution to another in a space of forward solutions using finite variations. Also, its purpose is to find the best mode based on the objective function<sup>9</sup>. Among the advantages and disadvantages of this local search algorithm, the researchers can respectively reach acceptable solutions in infinite space and stop them at local optimal points<sup>10</sup>. One of the advantages of the GA is its parallelism, which allows for the simultaneous consideration of multiple starting points for the problem, as well as the exploration of the problem space from multiple directions<sup>11</sup>. Moreover, among its disadvantages, GA can be used to investigate the problem space globally, and its local search is weak<sup>12</sup>.

GLS is a metaheuristic computational method for solving complex optimization problems using a solution that maximizes the criterion among multiple solutions<sup>13</sup>. GLS starts with a proposed solution and attempts to find the best solution

within the specific context of the current solution. If a better solution is found, the current solution is replaced, and the process continues from that solution<sup>13</sup>.

The PSO algorithm is employed in numerous optimization systems due to its reduced memory requirements and high computational efficiency<sup>14</sup>. Furthermore, its implementation and execution are more straightforward than those of other meta-heuristic algorithms. This algorithm has been successfully applied to numerous problems, including the identification of optimal points on standard criterion functions, the resolution of permutation problems, and the training of neural networks<sup>14</sup>.

The researchers who employed these algorithms in their studies were Wang, Broghany Bonfiglio and Li<sup>15-18</sup>. Moreover, among the studies that focused on optimising certain effective parameters in AC were those of Chang et al.<sup>19</sup> and Heidi et al.<sup>20</sup> pointed out that they optimized the thickness of the plate and the MPP structure of multilayer absorbers, respectively. Therefore, considering the importance of the parameters affecting the AC, the authors decided to conduct a study with the aim of comparing the methods of optimizing the parameters affecting the AC of aluminum metal foam with three methods of GLS, GA and PSO.

## Materials and Methods

The Lu model was invented by Lu et al. in 2000<sup>21</sup>.

In this model, the values of the variables are changed in a certain interval and the optimal value of the variables is found. The code of the Lu model selects the best solution from all possible values of the parameters<sup>21</sup>.

In a previous our study, the benchmarking method was used to validate the coding of Lu equations, and the value of  $R^2$  was 0.9<sup>22</sup>. The number of intervals for optimization was done by past studies according to the Table 1.

**Table 1:** The selected range of parameters affecting the AC optimization

| Thickness(L)[mm] | Porosity ( $\Omega$ ) %    | Pore size (D) [mm]         | Pore opening(d)[mm]       |
|------------------|----------------------------|----------------------------|---------------------------|
| 5,10,20,30 ,40   | $50 \leq \Omega \leq 95\%$ | $0.1 \leq D \leq 1.0$ [mm] | $0.01 \leq d \leq 0.1$ mm |

### Genetic algorithm (GA)

In a previous our study, the GA method was used for optimization<sup>22</sup>.

The GA is inspired by genetics and Darwin's theory of evolution and is based on the principle of natural selection, whereby the fittest survive<sup>23</sup>. In this algorithm, it performs automatic operations on a set of population (randomly) which has the same chromosome<sup>24</sup>. In a previous our study, in order to use this algorithm, the researchers created the initial population randomly by entering the parameters of the problem<sup>22</sup>. Then, they performed the crossover on the parents and the mutation and evaluated the answers and determined the best answer and the variables corresponding to it<sup>22</sup>. It should be noted that if the stop condition is met, the next step is implemented.

### Local search algorithm (GLS)

In a previous our study, the GLS method was used for optimization<sup>13</sup>.

GLS are widely used in a large number for hard computational problems, including computer science, especially artificial intelligence, mathematics, and engineering<sup>25</sup>. GLS is a modification that focuses on reaching the goal, and in this algorithm, the path and the cost of reaching are less considered. Also, this algorithm can be used as finding a solution to maximize a criterion among a number of possible solutions. This algorithm moves from one solution to another in a space of future solutions with the benefit of limited changes until a suitable solution is found. In a previous our study, in order to use this algorithm, the numerical solution of the Lu model problem was first addressed for validation<sup>13</sup>. In the second and third stages, coding was done with the GLS method using MATLAB software and determining the value of the optimal parameters<sup>13</sup>.

### Particle swarm algorithm (PSO)

In a previous our study, the PSO method was

used for optimization<sup>26</sup>.

PSO algorithm is an optimization method based on probability rules<sup>27</sup>. It was first coined in 1995 by Kennedy and Eberhart, inspired by the behavior of birds when searching for food. In this algorithm, first a set of initial answers is generated and then searching for the answer is done to find the optimal answer in the space of possible answers, or to time the generations. Each particle is defined multidimensionally with two values of position and velocity, and at each stage of the particle's movement, with two indices of velocity and position, the best responses are determined for all particles in terms of competence. Finding the best solution in the field of feature selection according to the global search strategy is one of the most important advantages of PSO<sup>27</sup>.

### Results

In GA, PSO and GLS, three physical parameters are optimized at different frequencies. The results of optimized AC using GLS, PSO and GA have been compared in thicknesses of 5, 10, 20, 30 and 40 mm. In this study, the low frequency is under 2 KHz, and the high frequency is above 2 KHz.

Figure 1 compares three optimization methods in thicknesses of 5 and 10 mm considering different ACs. According to figure 1a, three optimal methods with increasing frequency the AC is closer to 1. The increasing the thickness, the higher the AC is at low frequencies. The GLS method has a maximum thickness of 10 mm. Also, at frequencies under 2 KHz, the AC is less than 1.

In figure 1b, GA and PSO have the maximum AC at low frequency in 30 mm thickness. This is while the GA has the minimum AC at frequencies under 2 kHz in the thickness of 20 mm.

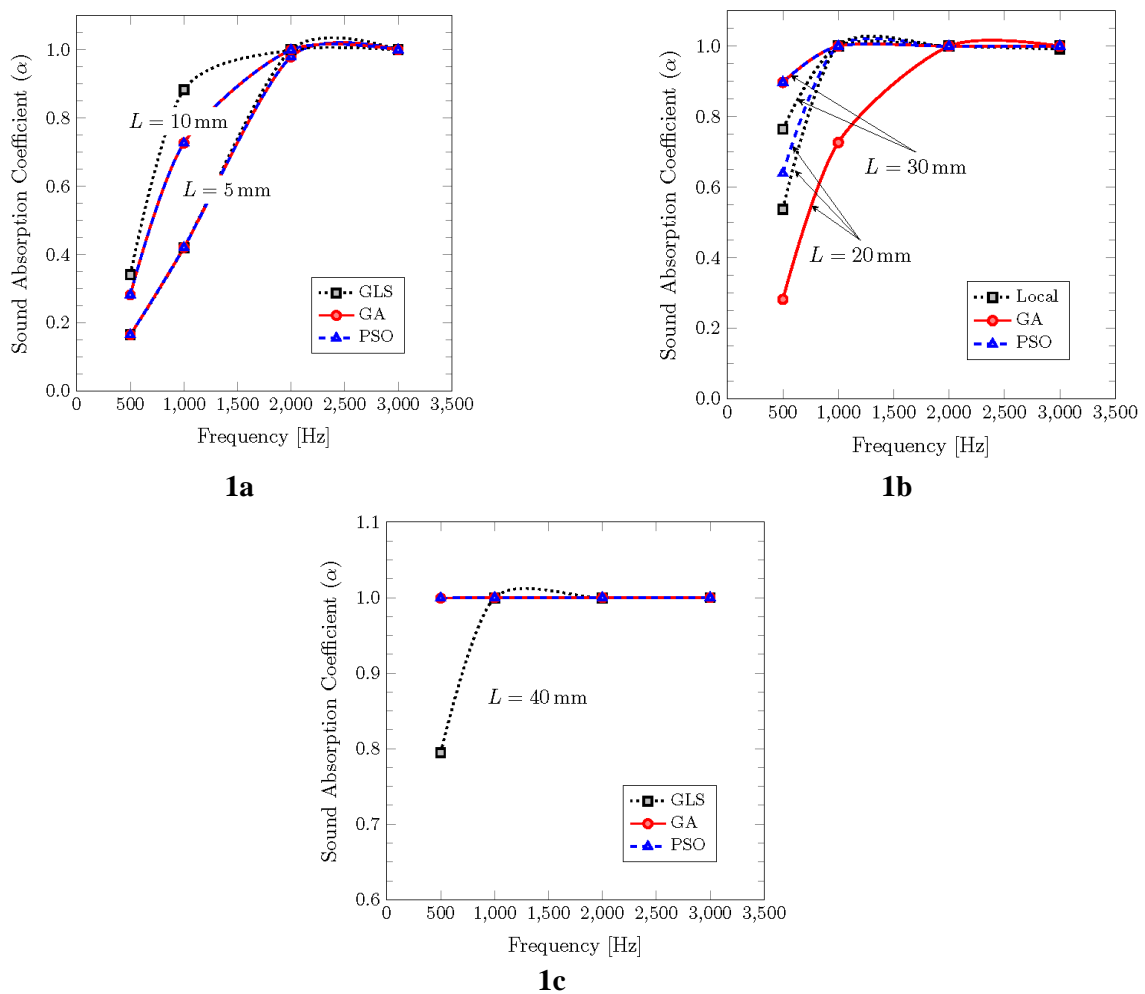
Figure 1c (40 mm thickness) indicated that the GA and PSO have the highest absorption in all frequencies, but the GLS method shows an AC of 0.8 at low frequencies.

Figure 2a showed the comparison of three methods at a low frequency of 500 Hz and in different thicknesses, where the GA method and PSO have an AC of 1 in thicknesses of 40 mm. As a result, it can be stated that GA and PSO have shown better performance with increasing thickness.

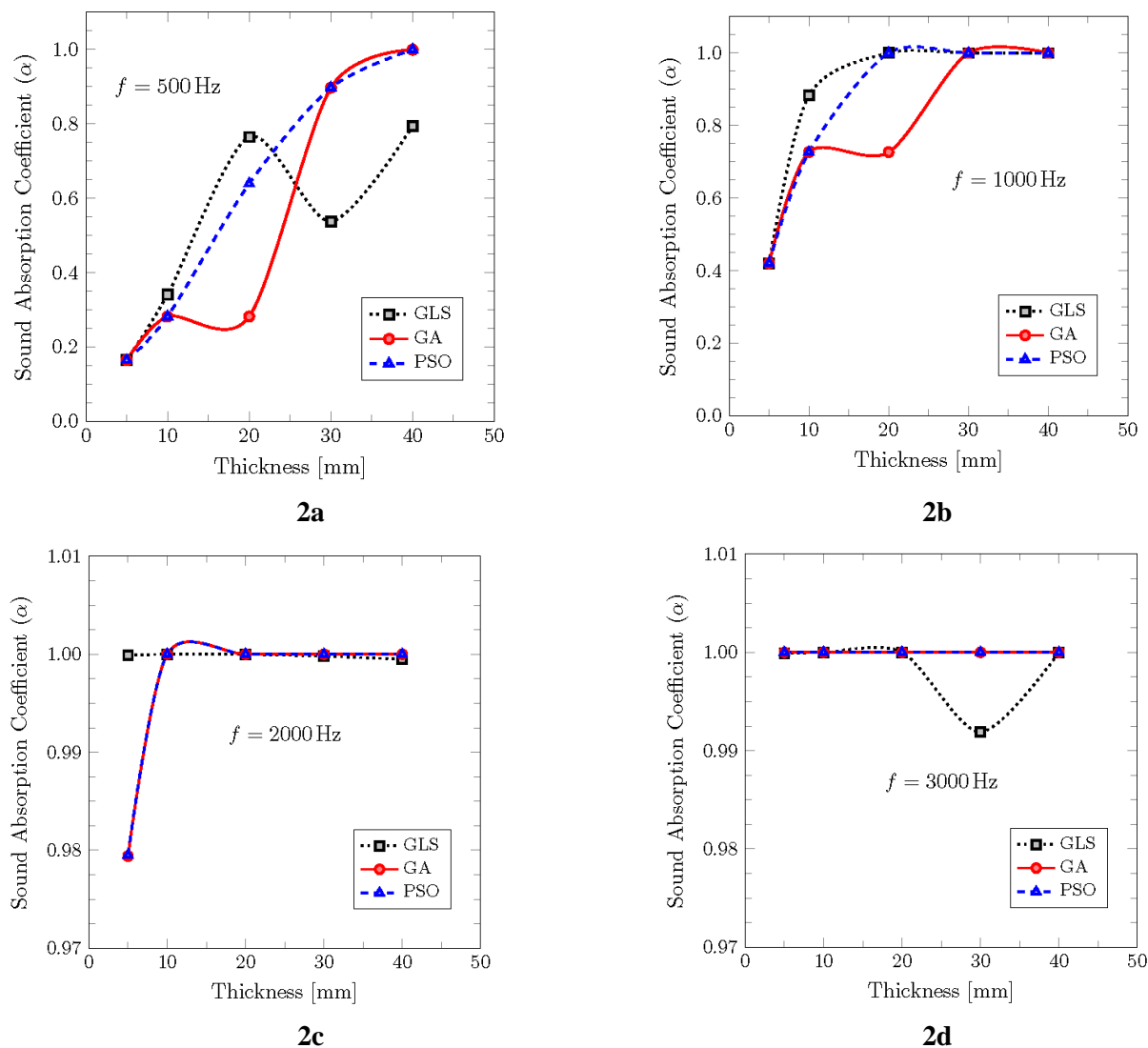
Figure 2b at a frequency of 1000 Hz showed that the GLS and PSO methods in thicknesses of 20, 30 and 40 mm have AC close to 1. In the GA method in thicknesses of 30 and 40 mm, the AC is close to 1.

Figure 2C at a frequency of 2000 Hz showed that the AC of the GLS method is close to 1 in the thicknesses of 5 to 40 mm. The AC of the GA and PSO in the thicknesses of 10 to 40 mm is close to 1.

Figure 2d at a frequency of 3000 Hz showed that the AC of the GLS method in thicknesses of 5, 10, 20 and 40 mm is close to 1. In the method of GA and PSO in thicknesses of 5 to 40 mm, AC is close to 1. In the thickness of 30 mm, a significant reduction is observed in the GLS method.



**Figure 1:** A comparative analysis of the AC of three GLS, GA and PSO models at thicknesses of 5 to 40 mm at different frequencies.



**Figure 2:** Comparison of AC regarding three GLS, GA, and PSO in frequencies from 500 to 3000 Hz with different thicknesses

The two methods of GA and PSO were suitable for optimizing the porosity parameter, pore size, and pore opening size at low frequency (500 Hz) and thickness of 40 mm.

### Discussion

Past studies used GA to optimize the design of absorbents. Broghany et al. in 2016, considered GA as an effective tool in optimizing the design of three-layer porous absorbent. The optimization results of their study showed that the three-layer porous structure with a thickness of less than one-fifth of the wavelength has better performance<sup>18</sup>. Also, the study by Lim et al. investigated and

compared three methods of GA, differential evolution (DE), and PSO for optimization, the results of which indicated that GA is faster than any other in obtaining the highest number<sup>28</sup>.

In this regard, other studies have also introduced GA as a success factor in many optimization problems, and this algorithm makes a more suitable choice to be made by searching for countless solutions from the problem area<sup>29</sup>. One of the advantages of the GLS is that it consumes little memory, which is usually a constant value can search for acceptable solutions in a large space, and obtain a favorable result<sup>30</sup>. Also, this



algorithm can always provide a reliable solution, even if it is interrupted at any time<sup>31</sup>.

The results of the present study showed that in three optimization methods, the AC increases with the increase of thickness at high frequency.

It can be reasonably assumed that an increase in absorber thickness will result in a corresponding increase in AC peak. It is understood that due to the long propagation distance in relatively thick samples, there is an increased interaction of the sound wave with the pore walls.

According to the studies, porous metal foam shows higher sound absorption behaviors than non-optimal samples at different frequencies using optimal morphology<sup>32</sup>. The study by Hakamada et al.<sup>33</sup> was also similar to this study. These studies stated that lack of apparent correlation between the pore size and the AC is due to the significant effects of the pore opening size, which is similar to the results of this study. Moreover, Navacerrada et al.<sup>34</sup> demonstrated that the cell diameter of metal foams stabilizes the properties of these materials, and the foams produced by infiltration technique are characterized by a very homogeneous structure and a high AC at low frequencies. In general, aluminum foam with a diameter of 0.5 mm is a good choice for applications. Through optimization design, in high frequency spectrum and medium, PM has better sound absorption properties. However, it has a weak absorption effect at low frequency. Therefore, in this study, it was stated that according to the actual sound spectrum, appropriate sound absorption materials should be selected<sup>15</sup>.

## Conclusion

In this study, the optimization tools of acoustic absorption parameters of porous metal materials are presented, which include GA, GLS, and PSO. The comparison of the present study with the results of the Lu model has confirmed the theoretical model in evaluating the performance of AC in the case of porous metal foam. The Lu model can be used as a tool for optimization of porous structures. The performance of GA and PSO is better than GLS at 500 Hz frequency, and

at frequency of 1000 Hz, GLS and PSO have an AC of close to 1 in thickness of 20, 30, and 40 mm, respectively. This is while the AC is close to 1 in the 2 kHz frequencies of the three methods. In the thickness of 10 to 40 mm, and at the frequency of 3000 Hz, GA and PSO perform better than the GLS.

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## Conflict of Interest

The authors declared no conflict of interests.

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## Code of Ethics

The study was approved by the university's Ethics Committee with ethics code of IR.SSU.SRH.REC.1400.022.

## Authors' contributions

The study's conception and design was carried out by Rohollah Fallah Madvari and Mohsen Niknam Sharak; data collection by Mohammad Javad Jafari and Faeza Abbasi; analysis and interpretation of results by Rohollah Fallah Madvari, Mohsen Niknam Sharak, and Mohammad Javad Jafari; drafting the manuscript by Rohollah Fallah Madvari, Mohsen Niknam Sharak, Mohammad Javad Jafari, and Faeza Abbasi. All the authors reviewed the results and approved the final version of the manuscript.

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