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Design of Tuneable Multifunctioning Metamaterial Absorbers using Progressive Neural Network Metaheuristics

T. Park, D. Noh, J. Park, J. Lee, S. Park, W. Choi and G. Noh

School of Mechanical Engineering, Korea University
Seoul, South Korea

Abstract

This paper presents a novel design optimization framework for a tuneable broadband mechanical metamaterial absorber (TBMMA). Utilizing a progressive neural network and metaheuristic algorithms, we capture the complex behaviour behind the mechanical properties and electromagnetic properties and enhance both microwave absorption and stiffness of octet-truss based metamaterial absorber. The proposed method leverages a multilayered octet truss structure with functionally graded approach, adjusting design variables such as strut diameter and aspect ratio to achieve optimal performance. This integrated approach demonstrates significant improvements in multifunctional properties with tunability through various optimization problems differed by operating frequency range, constraints for target design.

Keywords: octet-truss, multifunctioning metamaterials, progressive sampling, neural networks, metaheuristics, finite element analysis.

1 Introduction

The rapid advancement of electromagnetic wave technology has significantly increased electromagnetic pollution, leading to health hazards and electronic interference [1]. Traditional materials like carbon-based substances and ferrous nanoparticles, while useful for electromagnetic shielding, often struggle with limited effectiveness across wide frequency ranges and lack sufficient mechanical strength

[2]. This has led to a growing need for advanced materials that can efficiently absorb electromagnetic waves while maintaining structural rigidity.

Metamaterials, which are engineered structures with unique properties, have demonstrated significant potential in addressing these issues. Frequency selective surfaces (FSS) and periodic unit cells in metamaterials offer tuneable electromagnetic properties and multifunctional applications [3-5]. Nevertheless, it is challenging to create metamaterials that excel in both electromagnetic absorption and mechanical strength. This difficulty arises because the mechanisms behind microwave absorption and structural stiffening differ, leading to trade-offs requiring complicate multi-objective optimization techniques. Additionally, metamaterial absorbers can be tailored for specific purposes since the shape and topology of the base unit cell structure influence various properties, inducing adjustable framework to find the target-specific solutions for different usages.

This study proposes a novel tuneable broadband mechanical metamaterial absorber (TBMMA), further enhanced structures derived by octet-truss based metamaterial absorber presented by [6], designed to address these challenges. The proposed framework is applied to solve 2 different optimization problems and successfully find feasible solutions for given target purposes.

2 Methods

The primary objectives are to minimize reflection and maximize attenuation of electromagnetic waves, while also ensuring that the structure maintains its mechanical integrity under various conditions.

Electromagnetic wave absorption in materials is influenced by two key factors: impedance matching and attenuation constant. Impedance matching ensures that the incident wave enters the material with minimal reflection (decreasing $\mathbf{S}_{11}$), meaning that porosity of the metamaterials is important. Attenuation constant, on the other hand, can increase via to dielectric loss (increasing $\mathbf{A}$)property of radar absorbing materials, i.e. carbon black, therefore large amount of volume fraction required. Functionally graded approach through wave incoming direction proposed in [6] is adopted considering both impedance matching and dielectric loss. Therefore, electromagnetic wave absorption of the structure ($\mathbf{A}$) is defined by Equation (1) where S_{11}, S_{21} are reflection and transmission, respectively.

$$|\mathbf{A}|=1-|\mathbf{S}_{11}|^2-|\mathbf{S}_{21}|^2 \tag{1}$$

The mechanical performance of the TBMMA is critically determined by its structural design. As the density of porous microstructure decreases, stiffness decreases exponentially with a scaling factor n about 2 or 3. Scaling factor close to 1 implies that degradation of stiff properties of backbone materials are linearly conserved with the given microstructure. Therefore, we defined the relationship between relative density ρ and relative modulus (stiffness) E with Equation (2) to characterize the mechanical property of octet-truss based TBMMA, where b is modulus constant for a specific structure [7].

$$E=b\times\rho^{n} \tag{2}$$

The main objective of optimization is to seek an ideal set of design variables (DR, AR, θ, wt%) that maximizes the microwave absorption capability of the structure while maintaining the mechanical properties of the underlying metamaterial. Consequently, multifunctional properties are achieved by prioritizing electromagnetic performance as the target objective function and mechanical performance as the constraint. Taking into account the Equation (3-5), the minimization problem can be framed as follows:

$$\min G(DR, \theta, AR, wt\%, \mathbf{f}) = 100-A \tag{3}$$

$$\begin{gathered} n(AR, \theta)<n^{*} \\ \rho(DR, AR, \theta)<\rho^{*} \\ E(AR, \theta)>E^{*} \end{gathered} \tag{4}$$

$$\begin{gathered} 0.05<DR<0.175 \\ -0.4<AR<0.4 \\ 0<\theta<0.015 \\ wt\%=2.5\%, 5\%, 7.5\%, 10\% \end{gathered} \tag{5}$$

Figure 1 describes the variation of octet-truss unit cell structure through each continuous variable DR, AR, θ. As each of the three design variables independently alters the geometry of the base octet-truss structure, arbitrary combinations of these parameters can lead to a modified octet-truss structure with either a higher or lower volume fraction compared to the effects observed when each variable is adjusted individually.

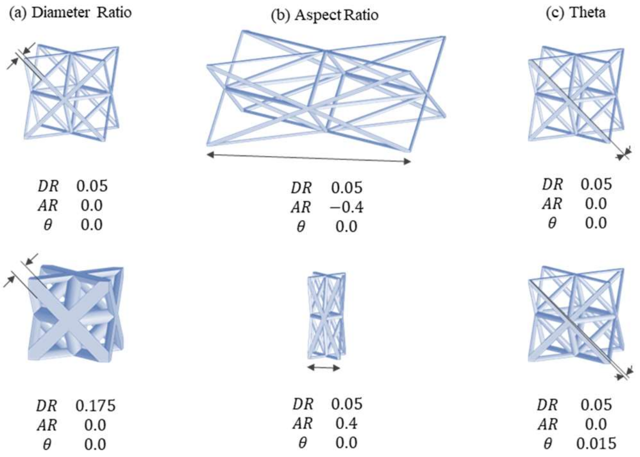


Figure 1: Parametric design space description for octet-truss structure.

We constructed two finite element models simulating the compression test and microwave absorption experiments. Figure 2 shows the FEA setups for two different experiments. In terms of mechanical performance, a compression experiment was conducted on a 5×5×3 unit cell structure with a rigid plate pressing on it. Finite element analysis was carried out using Abaqus/CAE 6.14. Symmetry conditions were applied to analyze only 1/4 of the actual structure in order to reduce computational costs. The elastic modulus of the PLA material was adjusted to 1091.8 MPa to account for inevitable defects in additively manufactured materials.

For electromagnetic properties, electromagnetic wave absorption was assessed using CST Studio Suite 2019 by varying carbon black concentration. The permittivity of carbon black-based filaments was determined experimentally using a Vector Network Analyzer in the 8 – 12 GHz range and extrapolated beyond this range. Electromagnetic wave absorption analysis was conducted on a 3 unit cell octet truss-based periodic boundary condition since the incident wave satisfies the far-field condition.

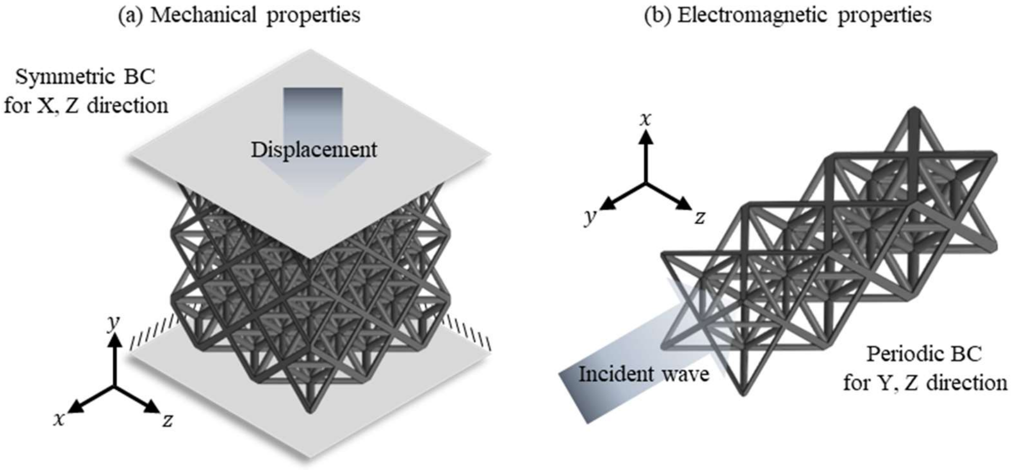


Figure 2: Finite element analysis for mechanical and electromagnetic property.

The numerical models based on FEA calculate relative density ρ, relative modulus E and absorbance **A**. by varying design variables. Since the FEA is computationally expensive to define the relationship between the mixed design space and the objective space, we applied Progressive Latin Hypercube Sampling (PLHS) [8] to sequentially construct train dataset from the previous database until the inference fulfil the stopping accuracy criterion. With PLHS algorithm, subset of Latin hypercube is added to the initial dataset at every iteration, then the union of subsets also satisfies the unique space-filling and non-collapsing property of Latin hypercube. Figure 3 shows the datapoints progressively sampled from mixed design space with 3 continuous variables and 1 discrete variable with 4 levels for iteration 1~3.

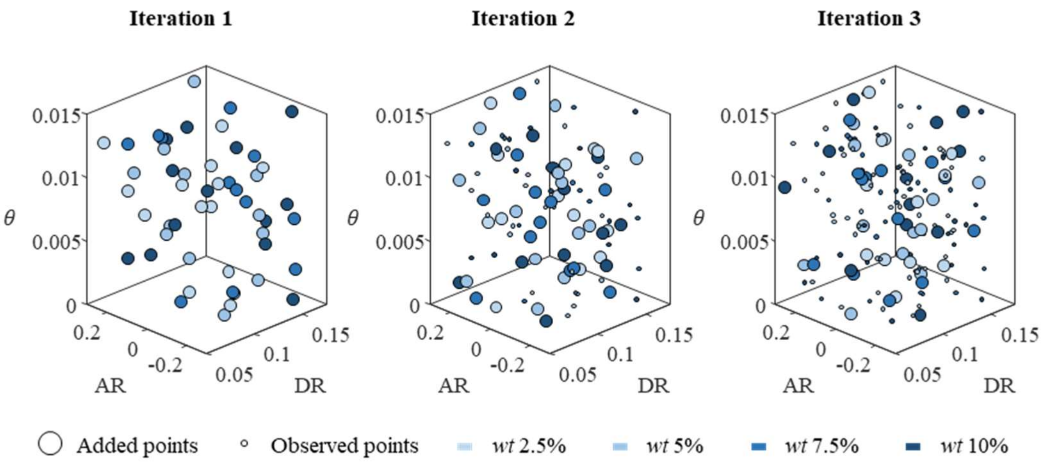


Figure 3: Data points progressively infilling the design space with PLHS.

Every iteration we generated FEA dataset and fitted the results to construct the output scaling factor n, relative density ρ, modulus constant b, and absorbance A. Then we used four well-trained multi-layer perceptron (MLP) based neural networks [9] to quickly evaluate performance for various design variables during optimization, greatly reducing computational costs to calculate the objective function and constraints in Eq. (3-4). Table 1 summarizes the performance of NN surrogate models with R^2 until every NNs exceed the value of 0.99 and Figure 4 shows regression analysis of FEA and NN results.

We employed Distance-Fitness Learning Teaching-Learning Based Optimization (DFL-TLBO) [10, 11], which mimics classroom teaching to efficiently solve constrained optimization problems with fewer parameters than methods like genetic algorithms, particle swarm optimization, and ant colony optimization. For our problems, we set the population size to 2000.

3 Results

We implemented 2 different optimization problems with different frequency band range and constraints. After 80 iterations, the optimization results were compared with neighboring values for the design variables. Optimization problem for Case 1 is defined by Equation (6-7).

$$\min G(\mathrm{DR}, \theta, \mathrm{AR}, \mathrm{wt\%}, \mathbf{f=5.8\sim18}) = 100-A \tag{6}$$

$$\begin{gathered} n(\mathrm{AR}, \theta)<1.5 \\ \rho(\mathrm{DR}, \mathrm{AR}, \theta)<0.3 \\ E(\mathrm{AR}, \theta)>0.05 \end{gathered} \tag{7}$$

Iteration	Dataset size	Network	Performance
1	68	**A**	0.9207
		n	0.9318
		ρ	0.9583
		b	0.9805
2	136	**A**	0.9725
		n	0.9553
		ρ	0.9983
		b	0.9855
3	204	**A**	0.9778
		n	0.9700
		ρ	0.9943
		b	0.9958
4	272	**A**	0.9808
		n	0.9727
		ρ	0.9972
		b	0.9966
5	340	**A**	0.9940
		n	0.9804
		ρ	0.9981
		b	0.9973

Table 1: Enhancement of surrogate model performance via progressive sampling.

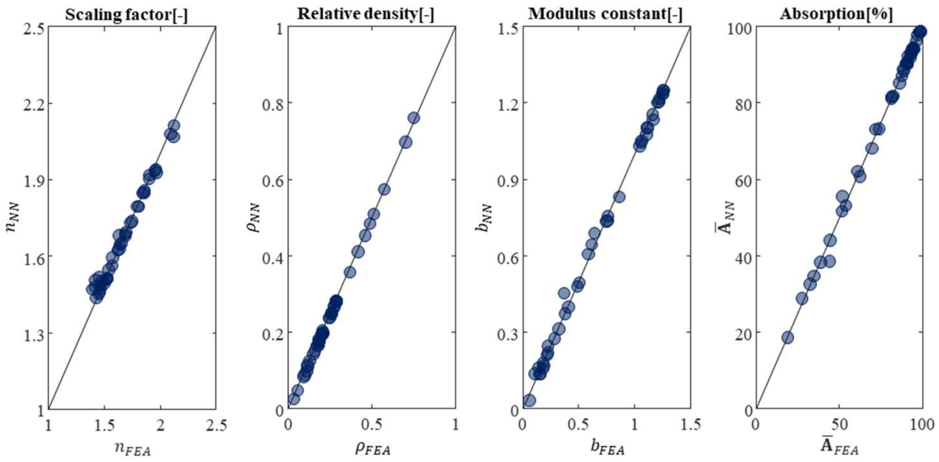
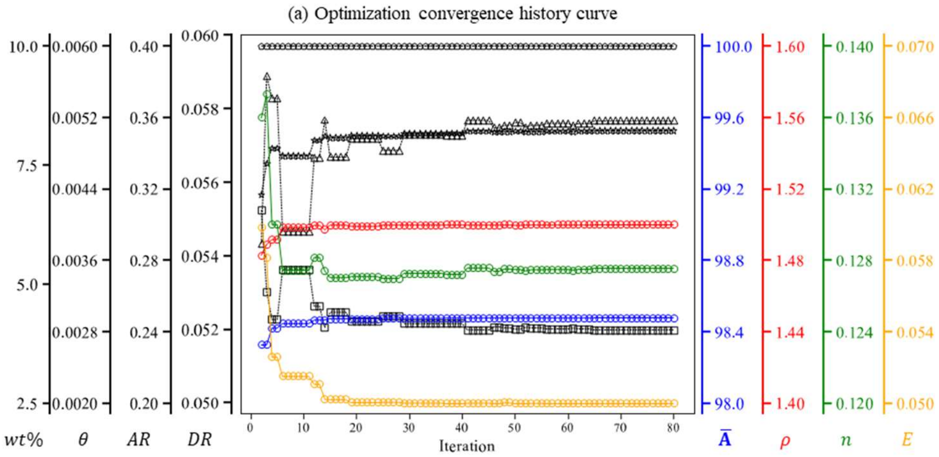
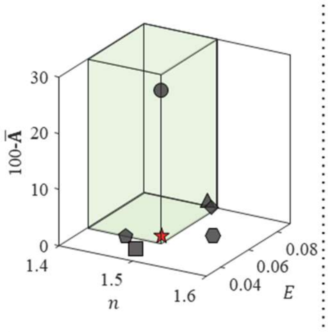


Figure 4: Regression analysis of FEA results and NN results.

Figures 5 and 6 summarize the results of two different optimization problems, respectively.


(a) Optimization convergence history curve

(b) Verification with test groups in the vicinity of the optimal design, Case 1



	★	▲	■	◆	⬟	⬢	●
DR	0.0577	**0.0702**	0.0577	0.0577	0.0577	0.0577	0.0577
AR	0.2410	0.2410	**0.1610**	**0.3210**	0.2410	0.2410	0.2410
θ	0.0050	0.0050	0.0050	0.0050	**0.0035**	**0.0066**	0.0050
wt%	10	10	10	10	10	10	**7.5**
n	1.500	1.500	1.497	1.512	1.468	1.552	1.500
ρ	0.1275	0.1783	0.1046	0.1700	0.1088	0.1498	0.1275
E	0.0499	0.0826	0.0337	0.0804	0.0414	0.0595	0.0499
$\bar{A}$	98.48	97.53	98.48	98.17	98.17	98.63	72.66

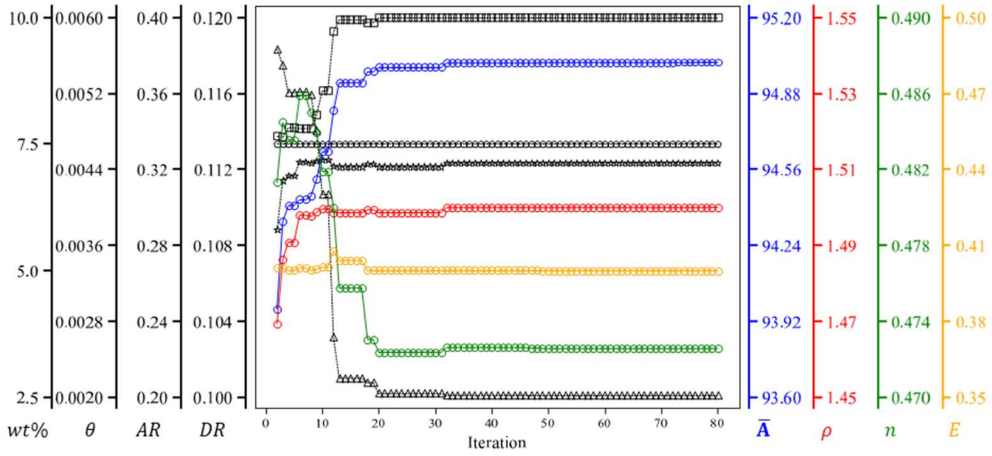
Figure 5: Optimization result for Case 1.

Similarly, optimization problem for Case 2 is defined by Equations (8-9).

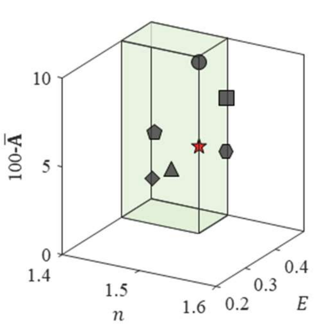
$$\min G(DR,\ \theta,\ AR,\ wt\%,\ \mathbf{f=12\sim18}) = 100\text{-}A \tag{8}$$

$$\begin{gathered} n(AR,\ \theta)<1.5 \\ \rho(DR,\ AR,\ \theta)<0.5 \\ E(AR,\ \theta)>0.4 \end{gathered} \tag{9}$$

For both cases, the proposed framework with progressive NN with metaheuristics successfully can find the solutions for different optimization problems, enabling tuneable design strategies for metamaterials absorber.


(a) Optimization convergence history curve

(b) Verification with test groups in the vicinity of the optimal design, Case 2



	★	▲	■	◆	⬟	⬢	●
DR	0.1001	**0.0876**	**0.1126**	0.1001	0.1001	0.1001	0.1001
AR	0.4000	0.4000	0.4000	**0.3200**	0.4000	0.4000	0.4000
θ	0.0045	0.0045	0.0045	0.0045	**0.0030**	**0.0060**	0.0045
wt%	7.5	7.5	7.5	7.5	7.5	7.5	**10**
n	1.500	1.500	1.500	1.494	1.451	1.525	1.500
ρ	0.4726	0.3971	0.5444	0.3651	0.4442	0.5009	0.4726
E	0.4000	0.3082	0.4946	0.2583	0.3759	0.4295	0.4000
Ā	95.01	95.34	93.29	95.44	94.40	95.43	90.28

Figure 6: Optimization result for Case 2.

4 Conclusions and Contributions

Through a combination of finite element analysis and Progressive Latin Hypercube Sampling, we efficiently navigate the mixed variable design space, enabling rapid and accurate predictions of performance metrics with minimal computational costs to evaluate the objective and constraints. By integrating these well-trained deep neural network surrogate models and population based metaheuristic optimization algorithms, we systematically optimize key design variables to achieve superior performance using a multilayered octet truss structure.

The proposed framework can be applied to various design procedures incorporated with stiff and lightweight metamaterials absorber embedding applications and extended to other problems not only with different physics but also with different parameterized unit cell structures for numerous engineering field, expected to serve as a key feature for data-driven computational mechanics techniques.

Acknowledgements

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