Kolmogorov-Arnold Network-Aided Design of Conch Shell-Inspired Acoustic Metamaterial for Rail Noise Mitigation

JIA-HAO LU, SI-QI DING and YI-QING NI

ABSTRACT

Urban transportation noise has become a critical challenge for modern cities striving to maintain an acceptable acoustic environment and ensure public well-being. Traditional noise mitigation approaches, such as bulky barriers and thick soundproofing panels, often struggle to balance broadband and high-efficiency sound absorption with lightweight, thin-layer configurations. Acoustic metamaterials (AMMs) offer a promising alternative, enabling high-efficiency sound absorption across broad frequency ranges with reduced weight and thickness. In addition, incorporating biomimicry into the design of AMMs allows us to draw inspiration from the natural structures like conch shells with remarkable sound-dampening properties due to their unique geometries and material compositions. By mimicking these natural designs, we can create AMMs that not only enhance sound absorption but also maintain lightweight and compact configurations. However, the bio-mimic AMM design is often complex, computationally expensive, and requires intricate geometric layouts and multi-parameter optimization. In this study, we propose a novel design framework to address the design challenges associated with conch shell-inspired AMMs by combining machine learning and optimization algorithms. Our framework uses Kolmogorov-Arnold Networks (KANs) to model and predict the acoustic absorption performance based on various geometric and material parameters, specifically targeting the 500–2000 Hz frequency range, which encompasses many of the most disruptive frequencies in rail transport. Particle swarm optimization (PSO) then guides the design towards configurations that achieve average absorption coefficients above 0.80, while minimizing simulation complexity and computational cost. Compared to conventional noise control solutions, this framework significantly reduces volume and complexity without compromising acoustic absorption, making it more viable and cost-effective for train noise abatement. Moreover, by shortening design cycles and reducing iteration costs, our approach can accelerate the development of next-generation noise mitigation acoustic materials, holding a significant promise for creating quieter, more sustainable, and more efficient rail systems.

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INTRODUCTION

Urban transportation noise has become a critical environmental challenge in modern metropolitan landscapes, significantly impacting public health, quality of life, and urban sustainability [1]. Particularly, rail transportation generates complex acoustic emissions across multiple frequency ranges that penetrate urban environments, causing substantial noise pollution [2]. Traditional noise mitigation strategies, such as massive sound barriers and thick soundproofing panels, have proven inadequate in the developing industry due to their limited effectiveness, substantial weight, and considerable spatial requirements [3].

Acoustic metamaterials (AMMs) represent a promising technological frontier in noise control, offering capabilities to manipulate sound wave propagation through innovative structural designs [4]. Drawing inspiration from nature's inherent sound-dampening systems, researchers have begun to develop biomimetic AMMs that mimic the intricate structures found in biological systems [5]. The complexity of designing such advanced AMMs, however, presents significant computational and engineering challenges [6]. Traditional design approaches require extensive experimental iterations, multiple simulation cycles, and complex optimization processes, making the development of high-performance AMMs both time-consuming and resource intensive. This is where machine learning emerges as a new approach to materials design [7]. By leveraging advanced computational techniques, machine learning can accelerate the exploration of vast design spaces, identify optimal material configurations, and predict acoustic performance with high precision [8]. Specifically, deep neural network techniques offer powerful capabilities for modeling the complex, nonlinear relationships between material structures and their acoustic properties [21], enabling researchers to navigate the complex parameter spaces of AMM design more efficiently than ever before.

This study introduces an innovative biomimetic AMM that integrating melamine sponge's sound dissipation properties with the complex geometric resonance of conch shell-like cavity structures, targeting rail transportation noise mitigation. Utilizing Kolmogorov-Arnold Networks (KANs) and particle swarm optimization (PSO), we systematically optimize the material's structural parameters to achieve broadband high sound absorption performance (α>0.8) across the critical frequency range of 500–2000 Hz in transportation system.

DESIGN PRINCIPLE

The overall design of the AMM features a cylindrical sound-absorbing unit. The upper section is composed of a melamine sponge structure, engineered to provide sound absorption for mid to high frequencies, typically above 1200 Hz. This section leverages the sponge's porous characteristics to maximize sound energy dissipation. The lower section, designed to mimic the acoustic properties of the conch shell, targets mid to low frequencies ranging from 400 Hz to 1200 Hz. This dual-layered configuration ensures that the AMM effectively addresses a broad spectrum of sound frequencies, enhancing its applicability in various acoustic environments. Figure 1 illustrates the natural features of the conch-like and sponge-combined acoustic metamaterial. It visually represents the structural forms of both the conch and sponge, highlighting their contributions to the design.

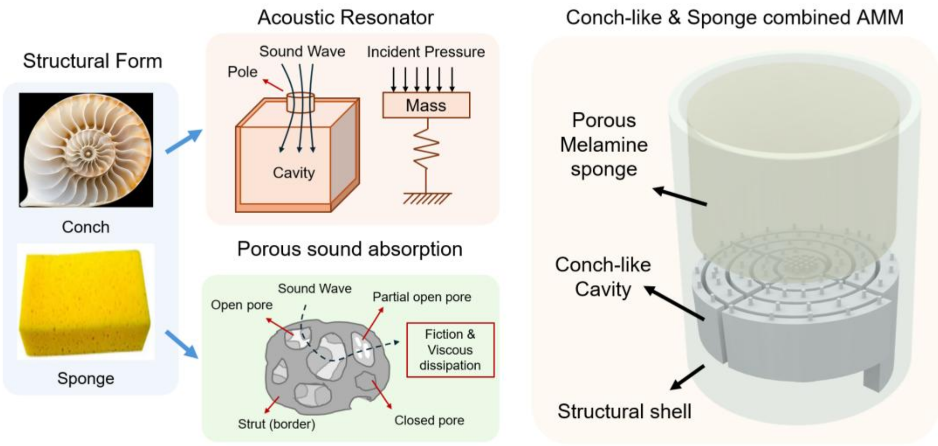

Figure 1. Natural features of conch shell-like & sponge combined AMM.

METHODOLOGY

We developed a finite element (FE) model in COMSOL Multiphysics to investigate the sound absorption characteristics of the AMM structure, integrating the thermos-viscous acoustics, pressure acoustics, and solid mechanics modules, as illustrated in Figure 2. The thermos-viscous acoustics module captures the internal cavity behavior, while the pressure acoustics module accounts for the porous module calculation and the propagation of incident sound waves in air, and the solid mechanics module models the AMM shell fabricated from commonly used additive manufacturing materials such as ABS. It is noted that the porous material we applied is melamine sponge using Johnson-Champoux-Allard (JCA) model to calculate its sound absorbing performance.

The detailed parameters of melamine sponge are listed at TABLE I. By combining these modules, we performed a parametric sweep across a frequency range of 10–2500 Hz at 10 Hz intervals, enabling calculation of global sound absorption coefficients. Different layer configurations were examined by varying four primary tunable parameters—sponge height H_s, cavity unit height H_c, hole depth D, hole diameter d. The cavity unit height is divided into 12 parts to construct a complex cavities structure.

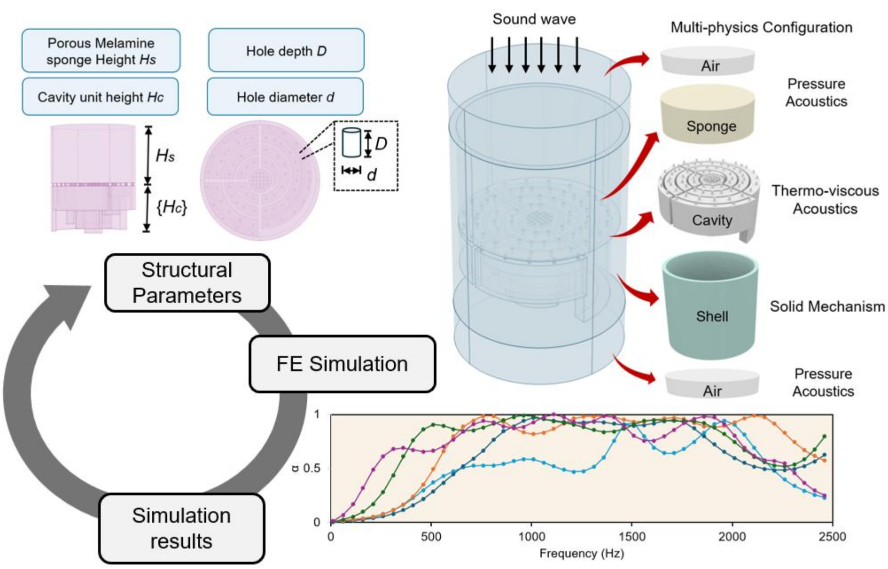

Figure 2. FE simulation process.

TABLE I. PARAMETERS FOR MELAMINE SPONGE

Parameters	Value
Porosity ε_p	0.995
Flow resistivity R_f	10500
Viscous characteristic length L_v	240
Thermal characteristic length L_{th}	470
Tortuosity τ_∞	1.0059

Considering that it is difficult to achieve the optimal sound absorption performance through FE analysis under a single, fixed set of structural parameters, we propose using a machine learning approach to establish a mapping between the structural parameters and the sound absorption coefficients to accelerate this process. Our dataset is derived from 500 COMSOL simulation results, with structural parameters as inputs. To reduce computational cost, the frequency range for calculating sound absorption coefficients remains unchanged, while the interval is reduced to 50 Hz, generating 40 data points from 50 to 2000 Hz per simulation as the labels for the dataset. The model employed is the KAN model, chosen because it effectively handles the complex nonlinear relationship between sound absorption coefficients and structural parameters, while also providing a mechanism to prune less significant connections. This accelerates the establishment of the mapping by retaining only the connections that exert more substantial effects. KAN proves particularly adept at capturing such nonlinear characteristics and is therefore well suited to processing multidimensional input data. The theoretical foundation of KAN derives from the Kolmogorov–Arnold representation theorem [11], whose expression is shown in,

$$f(x) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^{n} \phi_{q,p}(x_p) \right) \tag{1}$$

where Φ and φ are continuous functions. The core of this formulation asserts that, under sufficiently general conditions, any multivariate continuous function can be expressed as a finite sum of bounded, single-variable continuous functions via composition. This theorem demonstrates that high-dimensional continuous functions can be approximated or represented precisely through the composition of single-variable functions, without requiring explicit multidimensional expansions. The multilevel KAN model is described by,

$$KAN(x) = (\Phi_n \circ \Phi_{n-1} \circ \cdots \circ \Phi_2 \circ \Phi_1)(x) \tag{2}$$

where n represents the number of KAN layers. The machine learning module flow is illustrated in Figure 3(a).

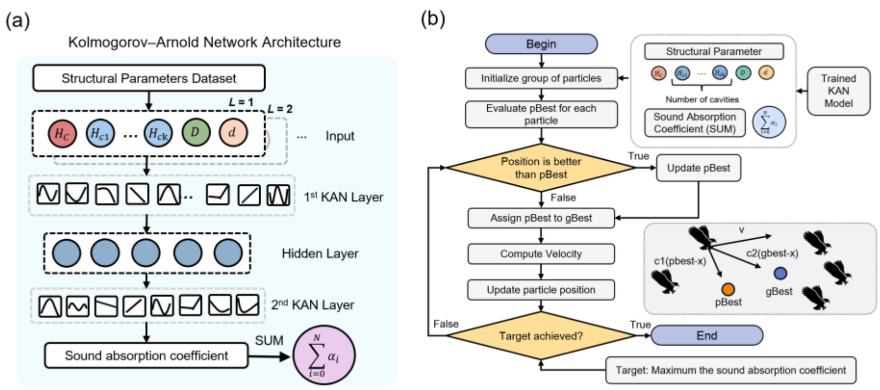

Figure 3. Machine learning & Optimization process. (a) KAN model architecture; (b) PSO process based on trained KAN model.

Once the KAN model has been thoroughly trained, it empowers the efficient creation of a robust search pool by merging the structural parameter matrix with the corresponding sound absorption coefficient matrix. This innovative approach generates a sufficiently large dataset, encompassing around 10,000 entries. In this dataset, the structural parameters are highlighted as the focal point for a subsequent optimization process, allowing for a comprehensive exploration of potential configurations.

To enhance the sound absorption performance, PSO technique is employed. The primary objective of this optimization is to maximize the sum of discrete sound absorption coefficients. This strategic approach aims to expand the frequency range of high sound absorption, which is crucial for applications requiring effective sound management across various environments. Figure 3(b) illustrates the PSO process based on the trained KAN model.

RESULT

The results provide a comprehensive overview of the model's performance and optimization outcomes. Figure 4(a) presents the loss curves for both the training and testing datasets, demonstrating a consistent and effective convergence for both sets. This indicates that the KAN model can learn the underlying patterns in the data without overfitting. In Figure 4(b), we compare the prediction performance of the trained model on the training and testing datasets. The results reveal a strong nonlinear fitting relationship, with an R^2 value of 0.9802 for the training set and 0.9285 for the testing set. These metrics underscore the advantages of the KAN model in this normalization task, highlighting its robustness in predicting sound absorption characteristics. The PSO optimization process is depicted in Figure 4(c), where a population size of 10,000 was maintained over 100 epochs. This extensive search led to the identification of optimal structural parameter combinations, which are crucial for achieving high precision in the design of acoustic metamaterials. The optimized parameters, suitable for simulation and production, are detailed in TABLE II, while maintaining the critical optimization targets illustrated in Figure 5(a). Notably, FE simulations conducted using these parameters yield sound absorption coefficient curves that closely align with the predictions from the KAN model. This correlation further validates the effectiveness of the KAN approach in accurately modeling the acoustic properties of the AMM, as shown in Figure 5(d).

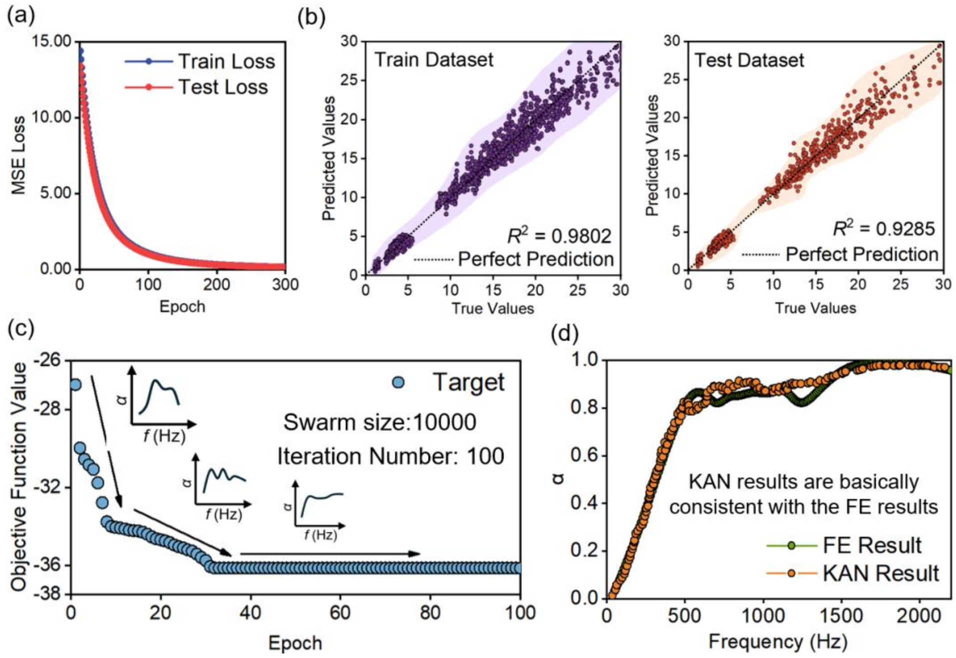

Figure 4. Machine learning and optimization results. (a) train and test loss; (b) prediction performance in train and test dataset; (c) PSO results; (d) results between KAN and FE in the best structural parameters configuration.

TABLE II. ADJUSTED STRUCTURAL PARAMETERS (UNIT: MM)

Parameters	Value	Parameters	Value
Sponge Height H_s	50	Cavity 5 Height H_{c5}	25
Total Conch Shell Cavity Height H_c	65	Cavity 6 Height H_{c6}	20
Hole Depth D	3	Cavity 7 Height H_{c7}	35
Hole Diameter d	1.5	Cavity 8 Height H_{c8}	25
Cavity 1 Height H_{c1}	5	Cavity 9 Height H_{c9}	39
Cavity 2 Height H_{c2}	5	Cavity 10 Height H_{c10}	3
Cavity 3 Height H_{c3}	5	Cavity 11 Height H_{c11}	25
Cavity 4 Height H_{c4}	10	Cavity 12 Height H_{c12}	25

After the machine learning and optimization process, we conducted complete FE simulations using this parameter set to evaluate the sound absorption coefficient, as depicted in Figure 5(b). The results indicate that the optimized AMM achieves a sound absorption coefficient exceeding 0.8 within the frequency range of 500 Hz to 2000 Hz, with values approaching 1.0 beyond 1500 Hz. This performance is attributed to the effective integration of a composite cavity mimicking a conch shell, which addresses mid-low frequencies, and a porous sponge that absorbs mid-high frequencies, thereby achieving impedance matching. The normalized acoustic impedance and reactance, shown in Figure 5(c), reveal a consistent trend in the acoustic impedance, remaining above 0.15 throughout the frequency range. Starting from 250 Hz, the impedance increases from 0.2 to a peak of 0.4 at 600 Hz, followed by a gradual decline to a minimum of 0.18 at 1250 Hz, before rising again to 0.32 at 2000 Hz. The normalized acoustic reactance exhibits a steady upward trend, transitioning from -1.1 at 250 Hz to -0.4 at 450 Hz, maintaining a plateau until 1250 Hz, and subsequently approaching zero while remaining relatively stable. This relationship between the sound absorption coefficient and the variations in acoustic impedance and reactance suggests that the optimized AMM effectively manages energy dissipation and resonance phenomena, contributing to its high absorption performance. Figure 6(d) illustrates the transmission loss, which increases from approximately 40 dB at 250 Hz to around 63 dB at 1200 Hz, ultimately reaching about 70 dB at 2000 Hz. It is important to note that these values represent a trend rather than actual transmission loss in practical applications, as real-world scenarios typically do not exhibit such high decibel losses.

The sound pressure distribution visualization in Figure 6 offers critical insights into the energy dissipation mechanism. At lower frequencies (200-400 Hz), no negative pressure regions are observed. Progressively, from 600 Hz onwards, negative pressure zones emerge within the conch-shell-inspired multi-cavity structure, indicating primary resonance contributions. Beyond 1200 Hz, these zones migrate to the porous sponge structure.

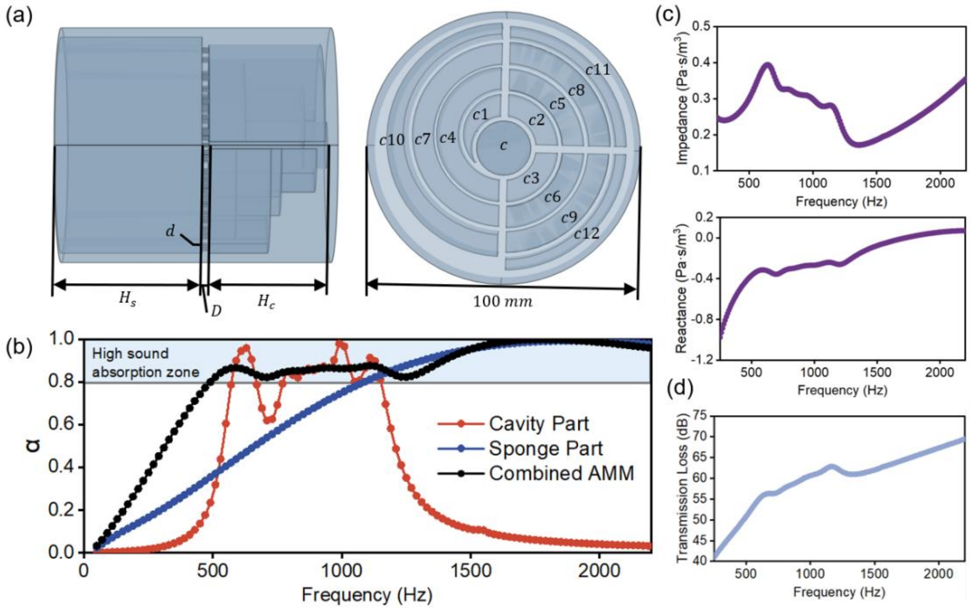

Figure 5. Sound absorption performance of optimized AMM. (a) structural parameters target distribution; (b) sound absorption coefficient; (c) normalized acoustic impedance and reactance; (d) transmission loss.

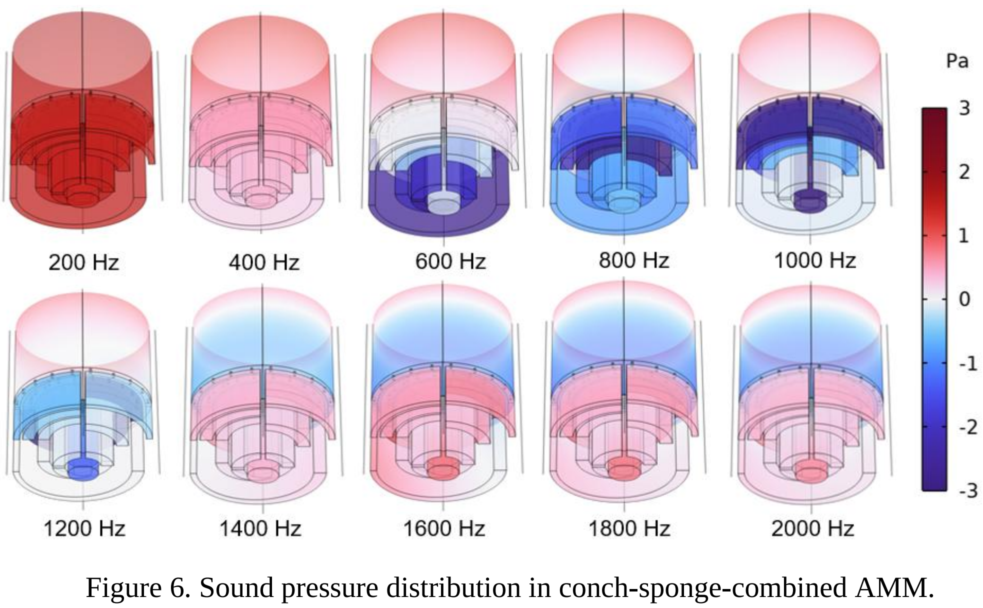

Figure 6. Sound pressure distribution in conch-sponge-combined AMM.

CONCLUSION

This study presents a novel approach to AMM design, leveraging biomimetic principles and advanced machine learning techniques to address urban transportation noise challenges. By integrating conch shell-inspired cavity structures with porous sound dissipation mechanisms and employing KAN with PSO, we have developed an AMM that achieves broadband sound absorption. The optimized design consistently demonstrates absorption coefficients exceeding 0.8 across the critical 500-2000 Hz frequency range, significantly outperforming traditional noise mitigation strategies. Our methodology not only provides a framework for advanced acoustic material development but also demonstrates the potential of interdisciplinary approaches combining machine learning, biomimicry, and materials engineering in solving complex acoustic challenges.

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