Applied Acoustics 87 (2015) 103–108

Contents lists available at ScienceDirect

Applied Acoustics

journal homepage: www.elsevier.com/locate/apacoust

Acoustic performance of aluminum foams with semiopen cells

Dong Guan [a], Jiu Hui Wu [a,*], Jiangling Wu [b], Jing Li [a], Weitao Zhao [a]

[a] School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, China
[b] School of Highway, Chang'an University, Xi'an 710064, China

ARTICLE INFO

Article history:
Received 30 November 2013
Received in revised form 13 April 2014
Accepted 20 June 2014
Available online 18 July 2014

Keywords:
Aluminum foams
Sound absorption
Bulk density
Static flow resistivity
Generalized regression neural network

ABSTRACT

To evaluate the effects of structural parameters on sound absorption performance of the aluminum foams with semiopen cells, a generalized regression neural network (GRNN) model has been utilized. In this paper, parameters of bulk density, static flow resistivity were analyzed. Results indicate that the effects of bulk density on sound absorption properties of the semiopen-celled foams are limited. On the contrary, the effects of static flow resistivity on absorption coefficients are complicated. When frequency is 500 Hz, there has no significant relationship between static flow resistivity and sound absorption coefficients. When the frequency is higher than 1000 Hz, with flow resistivity increasing, absorption coefficients of the aluminum foams increased significantly from 0.2 to exceed 0.8. However, when the static flow resistivity reaches 140 kPa s/m^2, still increasing static flow resistivity could not improve the acoustic performance. Analysis revealed that the GRNN model provides a robust method for predicting acoustic absorption properties.

1. Introduction

Common porous materials can be used in noise control engineering including polyurethane foam, mineral fiber composites and glass fiber felts [1]. An extensive experimental as well as theoretical literature exists for porous materials [2,3]. Besides them, there are various types of new porous materials could be used to absorb the noise as well. Due to the properties of low specific weight, high specific stiffness, not inflammable, good machinability, good acoustic and mechanical damping, aluminum foams are widely used in transportation, national defense and other fields [4–10]. Generally speaking, aluminum foams can be classified into open-cell foams, closed-cell foams and semiopen-cell foams based on the three kinds of connectivity among the cells [11,12]. Cells are connected to each other with air in the open-cell foams and they are isolated by a wall of thin aluminum film in closed-cell foams. On the contrary, cells of the semiopen aluminum foams are interconnected by the small circular openings with sizes adjustable [12]. Typical structure of the semiopen-cell aluminum foams is shown in Fig. 1 and each cell could be regarded as a Helmholtz resonator. The foams are fabricated by a negative pressure infiltration method and the details could be seen in Ref. [13]. Acoustic properties of the aluminum foams with dead-end porosity were tested by Dupont et al. [14]. Results show that they were not in accordance with the classical fluid model predictions such as the Johnson–Champoux–Allard model. Two acoustic models were developed by Dupont, one for non-symmetric and the other for symmetric dead-end porous aluminum. These two models can be used to study the acoustic absorption and sound transmission properties of the dead-end aluminum foams. Han et al. [15] studied the sound absorption behavior of the open-cell aluminum foams prepared by the infiltration process. The dissipation mechanism of sound in the open-cell foams is mainly viscous and thermal losses when there is no air-gap backing. However, Helmholtz resonant absorption will become the predominantly dissipation approach when there is an air-gap backing. A combined experimental and theoretical study of the sound-absorption applications aluminum foams with semiopen cells was presented by Lu and his colleagues [12,16]. Normal sound absorption coefficient and static flow resistivity of the six samples which have different porosities, pore sizes and pore openings were measured. An acoustical model which assume as an ideal honeycomb structure was developed by Lu et al. The calculated theory was based on the acoustic impedance of the circular openings and cylindrical cavities due to viscous effects as well as the electro-acoustic analogy method. Theoretical predictions and experimental measurements were in good agreement.

Utilization of artificial neural network (ANN) in acoustic material has been carried out in recent years [1,17,18]. To predict the acoustical properties of polyurethane foams, a neural networks model was established by Gardner et al. [17]. The model is quite robust that it can be used to develop models for different materials

* Corresponding author. Tel.: +86 13572873296.
E-mail addresses: g1987d@sina.com (D. Guan), ejhwu@mail.xjtu.edu.cn (J.H. Wu).

http://dx.doi.org/10.1016/j.apacoust.2014.06.016
0003-682X/

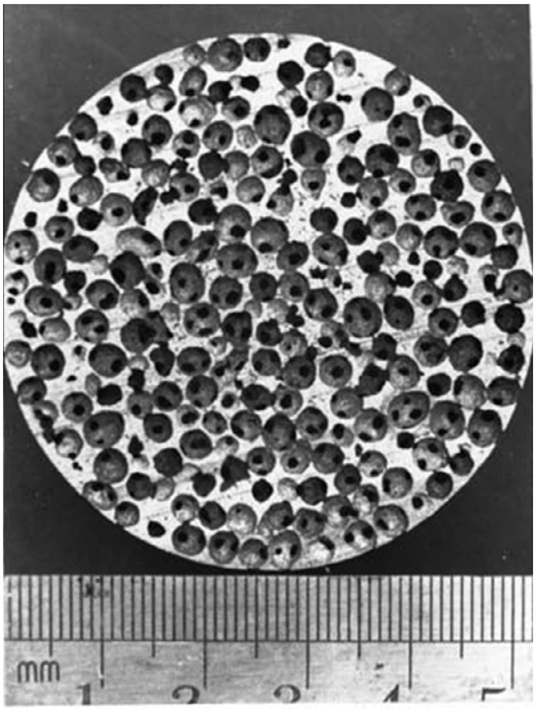

Fig. 1. Typical structure of semiopen aluminum foam samples [12] (50 mm in diameter).

with different parameters. Lin et al. [18] employed ANN algorithm to estimate the sound absorption coefficients of different perforated wooden panels which with various setting combinations including perforation percentage, backing material and thickness. Compared with ANN model, a multivariate linear regression (MLR) model was also developed. Results show that ANN is a useful and reliable tool for estimating sound absorption coefficients.

A general regression neural network (GRNN) model of the sound absorption for aluminum foams with semiopen cell is present in this paper. Bulk density and static flow resistivity were analyzed to investigate their effects on sound-absorption properties. Though the experimental data are less, GRNN model could provides a useful and reliable replenish to the numerical and analytical approaches.

2. GRNN model and the affecting factors

2.1. Generalized regression neural network

The general regression neural network (GRNN) was proposed by Specht [19] in 1991 on the basis of a standard statistical approach called kernel regression. A highly parallel structure and a one-pass learning algorithm were adopted in it. Even with very small amount of data in a multidimensional measurement space, the algorithm can provides smooth transitions from an observed value to another. It can be used for any regression problem even when the assumption of linearity is not justified. The GRNN model was applied to predict the sound absorption coefficients of sandwich structured nonwoven absorbers by Liu and his colleagues [1]. Estimation results show the prediction method is reliable and efficient.

Suppose $\boldsymbol{x}$ is a vector variable and y is a scalar random variable, $f(\boldsymbol{x}, y)$ represents the known joint continuous probability density function of them. Observed value of the random variable $\boldsymbol{x}$ is denoted by X, The regression of y on X is given by:

$$\widehat{Y}(X) = E(y|X) = \frac{\int_{-\infty}^{+\infty} yf(X,y)dy}{\int_{-\infty}^{+\infty} f(X,y)dy} \tag{1}$$

When the joint continuous probability density function of $f(\boldsymbol{x}, y)$ is not known, it must be reckoned from a sample of observations of $\boldsymbol{x}$ and y. For a nonparametric estimate of $f(\boldsymbol{x}, y)$, the class of consistent estimators proposed by Parzen will be used. Cacoullos shows it is applicable to the multidimensional case. A probability estimator of the function $\hat{f}(X,Y)$ is based upon the sample values of X_i and Y_i for random variables $\boldsymbol{x}$ and y. Where σ represents the smooth parameter, also called spread parameter, n denotes the number of observation samples and p is the dimension of the vector variable $\boldsymbol{x}$:

$$\hat{f}(X,Y) = \frac{1}{(2\pi)^{(p+1)/2}\sigma^{p+1}} \cdot \frac{1}{n}\sum_{i=1}^{n}\left\{\exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]\cdot\exp\left[-\frac{(Y-Y_i)^2}{2\sigma^2}\right]\right\} \tag{2}$$

Substituting the joint probability estimator function of $\hat{f}$ into Eq. (1) of the conditional mean and obtain the desired conditional mean of y given by X. Specifically, combining Eqs. (1) and (2) and interchanging order of the integration and summation yields the desired conditional mean of $\widehat{Y}(X)$:

$$\widehat{Y}(X) = \frac{\sum_{i=1}^{n}\exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]\int_{-\infty}^{+\infty} yf(X,y)dy}{\sum_{i=1}^{n}\exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]\int_{-\infty}^{+\infty} f(X,y)dy} \tag{3}$$

The Gaussian function of D_i is expressed as:

$$D_i = \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right] \tag{4}$$

S_N and S_D is expressed as:

$$S_N = \sum_{i=1}^{n} Y_i D_i \tag{5}$$

$$S_D = \sum_{i=1}^{n} D_i \tag{6}$$

Substituting Eqs. (4)–(6) into Eq. (3), obtain the following formula:

$$\widehat{Y}(X) = \frac{S_N}{S_D} \tag{7}$$

The GRNN model constructed by Eq. (7) is shown in Fig. 2. It consists of four layers of neurons including input layer, pattern layer, summation layer and output layer. Input layer is the distribution units, which receives message and stores the input vector of X_i, the number of its neurons equals to the dimension of the input vector n. Pattern layer receives the message from input layer and then a nonlinear transformation is carried out from the input layer to the pattern layer by Eq. (4). Each unit in the pattern layer represents a training pattern. There are two neurons in the summation layer: the first neuron sums all the outputs of the pattern layer and evaluates the numerator of Eq. (7), and the neurons from

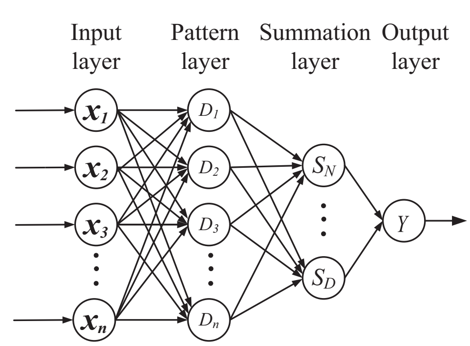

Fig. 2. GRNN architecture.