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A DATA-DRIVEN TWO-MICROPHONE METHOD FOR MEASURING THE SOUND ABSORPTION OF FINITE ABSORBERS

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ABSTRACT

A residual neural network is proposed to predict the sound absorption of an infinite rigidly-backed porous material from a classical two-microphone measurement above a finite porous sample. The network is trained using the microphones' transfer functions generated by a boundary element model (BEM), with a Delany-Bazley-Miki material model as a boundary condition. The network is validated numerically with BEM simulations and experimentally using two-microphone measurements of a baffled porous absorber of dimensions 60 cm$\times$60 cm and 30 cm$\times$60 cm, subject to various source locations. The results indicate that the network can significantly enhance the predictive capabilities of the classical two-microphone method. The suggested approach shows potential for accurately estimating the sound absorption coefficient of acoustic materials in realistic operational conditions.

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1. INTRODUCTION

The ability to characterize the absorption properties of absorbing materials is essential for a wide range of engineering applications. Standardized methods such as the impedance tube method [1, 2] or the reverberation chamber method [3] are limited to normal and random incidence, respectively. In contrast, angle-dependent absorption data can be obtained with *in situ* and free-field methods [4]. These methods typically rely on measurements of the sound pressure (and/or particle velocity) in the sample's vicinity [5–10] and on an analytical model of the sound field above the sample [4]. Existing models are based on plane-wave [5, 11, 12] or spherical-wave [6, 9, 10] assumptions and generally assume that the sample is infinite in extent. This assumption does not hold in measurements of realistic samples, and edge-diffraction effects result in erroneous absorption properties [13–19].

Several methods for modeling and mitigating edge diffraction effects have been proposed in the literature concerned with characterizing acoustic materials [18, 20–22]. In particular, a number of studies have employed machine-learning approaches to mitigate the edge effect based on measurements with an array of microphones [23, 24]. Other work utilizes machine learning techniques for efficient work with the impedance tube [25] and physics-informed neural networks [26].

This study introduces a deep-learning-based two-microphone approach to predict the angle-dependent sound absorption coefficient of finite-sized acoustic samples. Such an approach is of interest in that it only requires common instrumentation and a straightforward measurement procedure (the well-established two-microphone method [5]), unlike the more cumbersome approach in [23]. The proposed method uses a 1D residual neural network trained to predict the angle-dependent sound absorption coefficient from transfer function measurements. The network is trained and validated based on BEM-generated data [18, 23]. The validity of the proposed approach is examined numerically and experimentally using fibrous samples of different sizes and orientations. The results are compared with impedance tube measurements and analytical predictions from the two-microphone measurements.

2. METHODOLOGY

2.1 Datasets

2.1.1 Numerical datasets

For training and validation purposes, a numerical dataset is generated with a boundary element method (BEM) [18], following a procedure similar to that of [23]. The two microphones are located at 1 cm and 3 cm above the sample, which is assumed to be flush-mounted on a rigid baffle. The material properties are described based on a Delany-Bazley-Miki model [27]. The remaining BEM parameters span relevant values commonly found in practical scenarios: the sample sizes span from 20×20 cm^2 to 1 m^2, the thicknesses $d \in [5, 200]$ mm, the flow resistivity $\sigma \in [5, 100]$ kNs/m^4, the source distance $\|\mathbf{r}_q\| \in [1.2, 1.8]$ m, the source azimuth $\phi \in [0, 360)$ deg, and the source elevation $\theta \in [0, 80]$ deg. The frequency range is $f \in [100 : 10 : 2000]$ Hz. 50 000 instances were generated and split into $80 : 20$ for training and validation, and an additional 3 000 unique instances (not seen during training) were generated to test the network. More details on sampling these parameters can be found in [28].

2.1.2 Experiental datasets

We also performed eight two-microphone measurements with glass wool samples, model Focus A2 by Saint-Gobain Ecophon, of two sizes (60×60 cm^2 and 30×60 cm^2) to validate the method experimentally for various source distances and incidence angles. The samples were flush-mounted in baffles of medium-density fiberboard (MDF) panels. As in the BEM-generated training set, the microphones (model G.R.A.S. 40 PH) were placed 1 and 3 cm above the sample, and an omnidirectional sound source (model Monacor KU-516) emitted a 10-second-long sine sweep. A Brüel & Kjær Type 2706 amplifier and a National Instruments NI eDAQ-9178 digital acquisition system were used to collect the relevant time signals for postprocessing. The reader is referred to [28] for more details on these experiments.

2.2 Proposed neural network

A 1D residual neural network is designed to take two input features: (i) the complex-valued transfer function between the two microphones, and (ii) the source elevation angle θ, to predict the frequency-dependent sound absorption coefficients. The real and imaginary parts of the transfer function are treated as separate feature channels. At the same time, the elevation angle is skip-connected and concatenated with the latent space resulting from the network's convolutional layers. For precise network design and architecture details, the reader is referred to [28].

The network is trained for 250 epochs, using the mean squared error (MSE) as the loss function. The optimization was performed using an Adam optimizer with mini-batches of 64 samples and a weight decay of 10^{-3} [29]. The learning rate was set to 10^{-3} in the first 10 epochs and reduced exponentially by 0.9 from the 11-th epoch onwards. An early stopping criterion was imposed to prevent overfitting. In general, it is shown in [28] that training converges around 125 epochs.

3. EXPERIMENTAL HIGHLIGHTS

The network predictions were first evaluated using only numerical data, that is, in the same form used for training. As mentioned in section 2.1, 3000 examples unseen by the network during training were used for testing the predictions. With an MSE of $8.42 \cdot 10^{-5}$, the network provides accurate predictions of the sound absorption coefficient in various scenarios.

Figure 1 shows the network's prediction for the two measured glass-wool samples. Figs. 1a and 1d show two example results for normal wave incidence, with the curves "Miki model" viewed as the reference results. The network predictions underestimate the absorption coefficient somewhat, by less than 0.05 for the larger sample (Fig. 1a) and by less than 0.10 for the smaller sample (Fig. 1d).

Physical absorber samples were measured in an impedance tube to offer typical experimental reference results. Results are shown in Figs. 1b and 1e, with predictions based on simulated measurements on a smaller sample, Fig. 1b, and a larger sample, Fig. 1e. Note that somewhat longer source distances were used in Figs. 1b and 1e, compared to Figs. 1a and 1d. Again, the predictions by the network seem to underestimate the absorption coefficient somewhat, but the agreement is very good for the larger sample. It is worth noting that the impedance tube measurement values deviate somewhat above 1.5 kHz and may not be considered as true reference results.

Finally, traditional two-microphone measurement results for a smaller and a larger sample are presented in Figs. 1c and 1f, together with network predictions. Slightly longer source distances were used for this final comparison. For such small samples as were tested here, the finite-size effects are substantial, and it is clear that the network predictions suppress these interference effects completely. For instance, owing to the intrinsic nature of the training of the network, the method inhibits the emergence of negative absorption values.

Finally, the consistency of the network predictions for varying source distances should be emphasized, as only marginal differences within the rows can be observed.

4. CONCLUSION

Based on a deep-learning-based two-microphone approach, we predict the angle-dependent sound absorption coefficient of finite-sized acoustic samples utilizing well-established measurement procedures and a one-dimensional residual neural network. More concretely, appropriate boundary element method simulations, assuming a Delany-Bazley-Miki material model, provide the necessary database for the network training and validation within a frequency range of interest between 100 Hz and 2 kHz. In addition, suitable measurements of fibrous samples of different sizes and orientations provide the transfer functions to validate the methodology. Comparing the results of the analytical model, the impedance tube measurements, and the prediction based on the neural network, one finds a high prediction quality concerning the analytical model and the impedance tube measurements. Furthermore, the neural network predictions toward the traditional two-microphone method are free from the typical edge diffraction effects, providing a suitable strategy for reliable absorption coefficient estimation. The proposed method aims to help engineers in room acoustics and material property identification accurately predict the sound absorption coefficients based on the well-known two-microphone measurement procedure without the common edge-diffraction errors.

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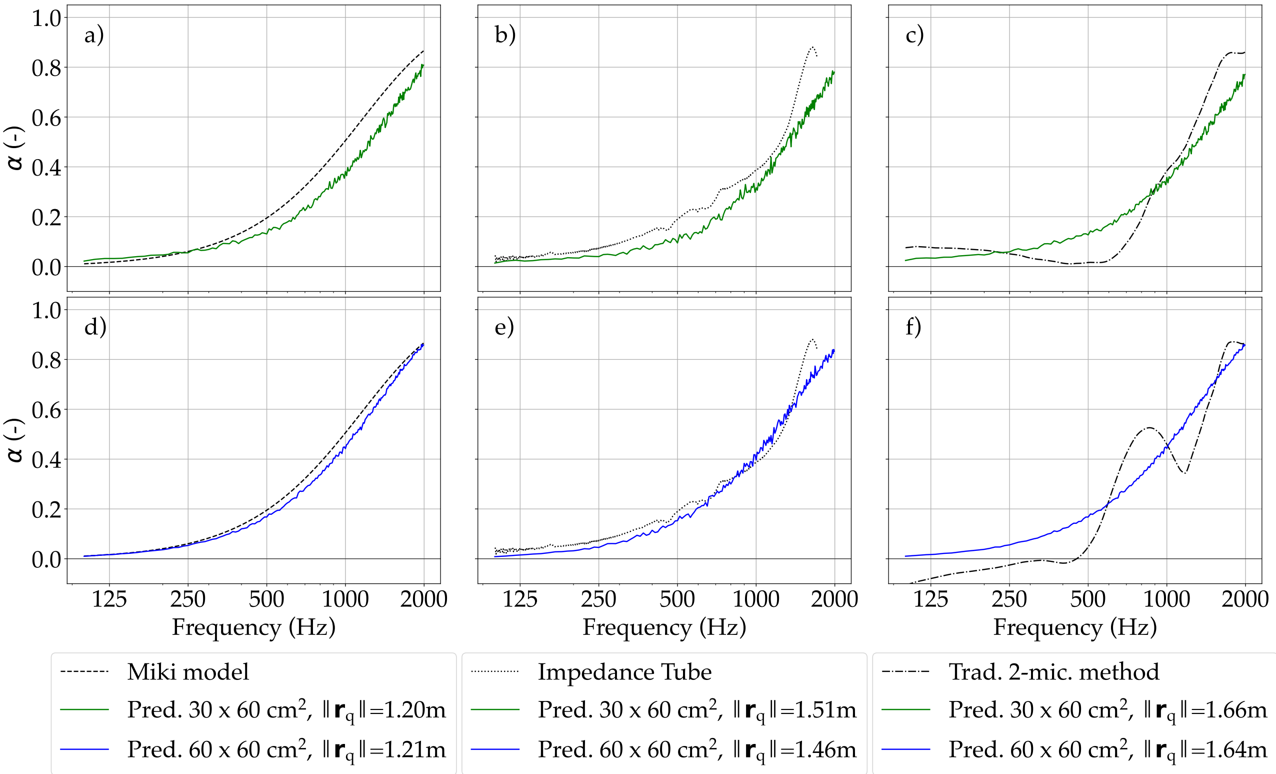

Figure 1. Predictions of the sound absorption coefficient for two samples at normal wave incidence and different source distances to the sample. Compared to Miki model with estimated flow resistivity of $54.7\,\mathrm{Nsm}^{-4}$ (a & d), impedance tube measurement (b & e) and the traditional two-microphone method (c & f).

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