Frequency-Domain-Based Parameter Identification of a Finite Element Vehicle Body in Vibroacoustics

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Introduction

Vibroacoustic excellence guarantees passenger comfort, as Gladwell stated in 1964 [1]. For this, uncertainties are important in the early development of vibroacoustics in a vehicle to avert expensive modifications close to the start of production [2]. Engineers must know which uncertain parameters are sensitive [3], and find reliable distributions of these sensitive input parameters for finite element simulations. This conference contribution provides a concise summary of the work presented in [4] , which addresses the challenge of determining uncertain parameters and their distributions in a large-scale vibroacoustic finite element model based on data in the frequency domain using neural networks.

Simulation Model, Data, Methods, and Evaluation

We present the simulation model, the data, the methods, and the evaluation of the neural network performance in the following.

Simulation Model

The finite element model of the vehicle has around 3 million elements, 3 million nodes, and 18 million degrees of freedom. The dimensions of vehicle finite element models are continuously expanding due to more precise modeling techniques [5]. This model comprises the body in white and several additional, simplified parts. Parameters such as mass, stiffness, positions of the center of gravity, and moments of inertia are uncertain, cf. [3; 4]. The simulation is a harmonic frequency response analysis performed within 20 Hz to 120 Hz. The mechanical admittance in the frequency domain, $Y_{kl}(\omega)$, is the parameter of interest. It is defined as the division of the velocity of the structure, $v_k(\omega)$, by the exciting force, $F_l(\omega)$, as following

$$Y_{kl}(\omega) = \frac{v_k(\omega)}{F_l(\omega)}. \qquad [Y_{kl}(\omega)] = \text{m/Ns} \qquad (1)$$

Data

Using Latin Hypercube Sampling, three data sets are generated with 170, 14, and 8 varied parameters. They consist of 100,000 simulations each. Data preprocessing includes logarithmic transformation for stiffness values, cf. [6], normalization, and standardization.

Methods

Fully connected neural network: A fully connected neural network is a type of artificial neural network where each neuron in one layer is connected to every neuron in the next layer, allowing for the propagation of information and the learning of complex non-linear relationships in the data. A detailed description can be found in [7; 8].

Convolutional neural network: A convolutional neural network is a specialized type of deep learning neural network designed to effectively process and analyze data by extracting hierarchical features by applying of learnable filters and pooling operations. We refer to [9] for more information.

Evaluation

Coefficient of determination: The coefficient of determination, denoted as R^2, is a statistical measure representing the proportion of the variance in the dependent variable that is predictable from the independent variable(s) in a regression model [10]. A value larger than 0.9 represents a significant performance of a neural network, cf. [11].

Results

We conduct a hyperparameter search with the package Hyperopt [12] using an approach of a specific grid search. Based on this hyperparameter search, we find the best settings for the fully connected neural networks, cf. Table 1.

Table 1: Optimized hyperparameter of the fully connected neural networks with 170, 14, and 8 parameters.

Optimized hyperparameter	170 parameters	14 parameters	8 parameters
Activation function	ELU	ELU	ELU
Loss function	Huber loss	Huber loss	Huber loss
Batch size	16	32	32
Layers	2	4	3
Neurons per layer	260	120	280
Learning rate	1e-5	1e-3	1e-3
Lowest coefficient of determination	-0.09	0.25	0.89
Highest coefficient of determination	0.57	0.89	0.98

For the 170-parameter data set, the fully connected feed-forward neural network exhibits poor performance, with a maximum coefficient of determination of 0.57. This coefficient is not good – generally, a coefficient of determination of 0.9 is required for a good-performing neural network [11]. Reducing the parameter set to 14 improves the coefficient of determination, reaching up to 0.89, but still not exceeding 0.9. For the 8-parameter data set, the fully connected feed-forward neural network achieves coefficients of determination between 0.89 and 0.98. The one-dimensional convolutional neural network further improves the results based on a hyperparameter search, cf. Table 2, with coefficients of determination between 0.95 and 0.99 for the 8-parameter data set. Further details are described in [4].

Discussion

The curse of dimensionality limits the performance of the neural networks for the larger parameter sets. The dataset of 170 parameters does not bring an acceptable result. It would be necessary to generate significantly more data to perform a parameter identification with a 170-parameter data set - so many that we can no longer recognize the benefit.

The convolutional neural network outperforms the fully connected feed-forward neural network. The best-performing model, the convolutional neural network with the 8-parameter data set, is used to generate histograms and probability density functions (PDFs) of the parameters based on artificial measurement data. With the presented process, engineers can use these reliable distributions in the vibroacoustic simulation of vehicle bodies under the consideration of uncertainties.

Table 2: Optimized hyperparameter of the convolutional neural networks with 8 parameters.

Optimized hyperparameter	8 parameters
Activation function	LeakyReLU
Loss function	Huber loss
Training batch size	64
Validation batch size	256
Output channels in the first convolutional layer	16
Output channels in the second convolutional layer	64
Output channels in the third convolutional layer	256
Hidden size in the fully connected layer	512
Kernel size	5
Dropout probability	0.24
Learning rate	1e-4
Lowest coefficient of determination	0.95
Highest coefficient of determination	0.99

Conclusion and Outlook

The presented method can deal with the challenge of determining uncertain parameters in a large-scale vibroacoustic finite element model based on data in the frequency domain using neural networks. The one-dimensional convolutional neural network with the 8-parameter data set provides the best performance, allowing the generation of histograms and PDFs of the parameters.

Future work includes using actual measurement data as input for the trained convolutional neural network. Another idea is to investigate other frequency ranges or load cases and explore other parameter identification methods for the complex NVH model.

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Disclosure

During the preparation of this publication, the authors used the AI language model Claude 3 Haiku, developed by Anthropic, to improve the readability of this work. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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