PROCEEDINGS of the
23rd International Congress on Acoustics

9 to 13 September 2019 in Aachen, Germany

Artificial Neural Network predicts noise transfer as a function of excitation and geometry

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Abstract

The Noise, Vibration and Harshness development of vehicle components still heavily relies on full vehicle tests. To reduce costs, the number of simulations is increasing. Commonly used simulation methods (Multibody-Simulation, Finite-Element-Method and Statistical-Energy-Analysis) are only valid within a limited frequency range and need high computational resources. The manually created models require validation through measured data. Holistic digitalization is therefore not achievable with today's simulation methods. Machine learning as a different approach lets an algorithm compute the physical relation between input and output. Once this relation is found, the trained neural network can predict the output to any new given input. Network architecture (e.g. number of layers, number of neurons) and hyperparameters (e.g. error function, backpropagation algorithm) are essential for the outcome. The network training is supported by Finite-Element computations.

Keywords: Machine Learning, Artificial Neural Network, Finite-Element-Method, Noise Transfer, Transfer Function

1 INTRODUCTION

The difficulty level of finding a mathematical description for a system and its behavior - a simulation model - increases with complexity. In order to find expressions for challenging relations, systems are commonly divided into subsystems [11]. A widely spread approach to calculate the dynamics of mechanical components is the Finite-Element-Method (FEM). The model creation itself is a manual and time consuming process that relies on experience. Once the model is defined, the excitation can be processed to calculate the response. Figure 1 illustrates this conventional approach and compares it with a data-driven process. In difference to the conventional approach, it approximates the model through a given excitation and response [5].

Conventional	Input (Excitation)	+	Model	=	Output (Response)
Data-driven	Input (Excitation)	+	Output (Response)	=	Model

Figure 1. Comparison of conventional and data-driven approach.

2 DATA-DRIVEN ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Network (ANN) approximates a function between a given input and an assigned output by solving a minimum problem [2]. This data-driven approach is commonly associated with Artificial Intelligence (AI). In AI, it belongs to supervised learning which is a subcategory of machine learning. Figure 2 shows a shallow ANN. This network consist of 3 input units, 3 hidden units and 1 output unit. Within the forward-pass, the weighted sum z_j is calculated for the given inputs x_i and the weights w_{ij}. The following activation function calculates the activation level y_j of the specific neuron in the hidden layer. Analogously repeating these steps for the output layer results in the network output y_k. Some of the most common activation functions in today's ANNs are the Tangens Hyperbolicus function (tanh) and the Rectified Linear Unit function (ReLU) [1]. By comparing the network output y_k with a target value t_k through a cost function, the network error E is calculated. In the backward-pass, this error is back-propagated for multiple inputs x_i, outputs y_k and target values t_k. For each iteration, the weights w_{ij} and w_{jk} are adjusted in order to minimize the cost function. The network training is completed once a global or local minimum is reached.

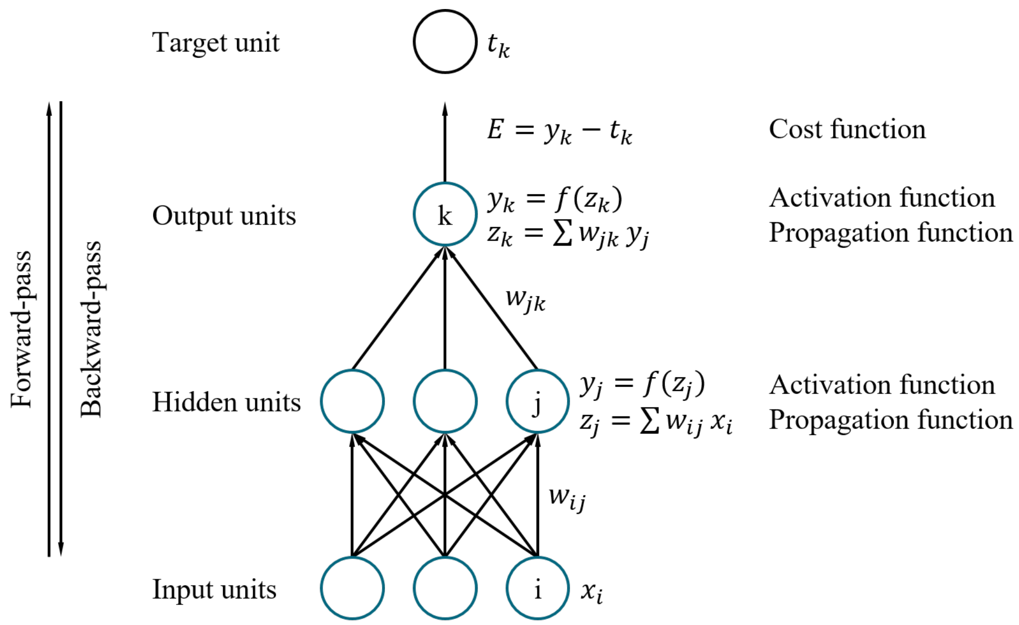

Figure 2. Artificial Neural Network consisting of 1 input layer, 1 hidden layer and 1 output layer.

The basic idea of neural networks goes back to 1943 when McCulloch and Pitts introduced a logical calculus for nervous activity [7]. In 1986, backpropagation for multi-layer perceptrons was published by Rumelhart et al. [9]. Affiliated with the latest breakthroughs in image-, video-, speech-, audio- and text-processing, deep learning networks with multiple processing layers are in the focus of today's research [6][10].

Within the domain of Noise, Vibration and Harshness (NVH), machine learning is used for a variety of tasks. Ranjbar and Marburg are reducing the radiated sound power levels of a rectangular plate by using a shallow ANN consisting of 5 hidden neurons [8]. A tire/suspension system and its dynamic behavior while being excited by road irregularities is simulated with Recurrent Neural Networks by Guarneri et al. They compare the calculations of the ANN to those from a Multibody-Simulation, concluding accurate results and a good computational efficiency [4].

3 TEST ENVIRONMENTS, EXCITATION, RESPONSE AND PREDICTION

In this article, we use the FEM-model in Figure 3 as simplified test environment. The coupled beams consist of a source side, a receiver side and 2 coupling brackets. The connectors are rigidly attached and have the distance x between each other. It is varied between 70 and 190 mm with a step size of 10 mm. This results in 13 different geometrical configurations. The left coupling is fixed in its position. Modeling was conducted in NX Nastran using 18 721 tetrahedron-elements with linear behavior. The excitation force F_z is applied on the source side with a frequency ranging from 0 to 6000 Hz. The response acceleration a_z is calculated for the receiver side. Excitation and response are oriented in z-direction. This process is repeated for different coupling conditions and excitations. In total, 1001 input- and output-spectra have been generated throughout the 13 different configurations (77 datasets per configuration). The generated database was then fed into an ANN-architecture in order to find a system description via machine learning.

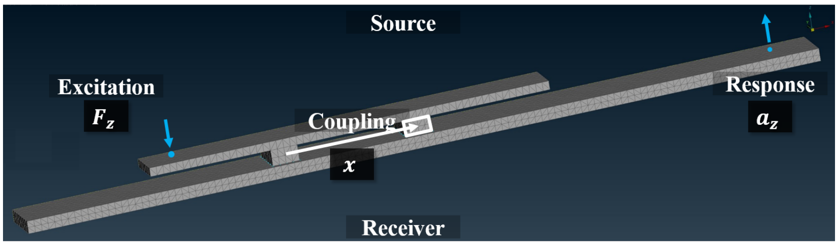

Figure 3. Source-receiver structure with excitation force F_z, response acceleration a_z and distance x between the connectors.

As ANN-architecture, a feedforward-topology is used that is visualized in Figure 4. The input vector consists of F_z and x from Figure 3. A fully connected hidden layer with 10 hidden neurons is used. As propagation function, the weighted sum is calculated according to Figure 2. The activation function in the hidden layer is tanh. The output layer is using the identity function. Both layers, hidden and output, are connected with a bias value. Since the input and output spectra range from 0 to 6000 Hz with a frequency resolution of 10 Hz, we trained 600 of the shown ANNs to approximate the system response for the entire spectrum. This allows us to use the explained ANN-architecture instead of having to process the complete spectral information with one large network.

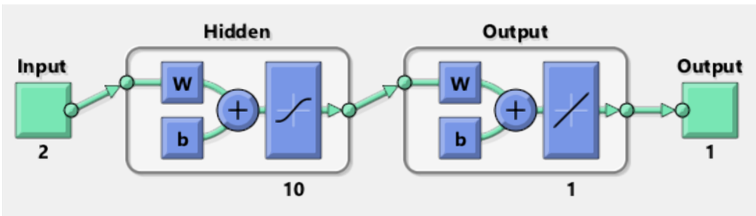

Figure 4. Feedforward-network consisting of 1 input-, 1 hidden- and 1 output-layer. The shown network has 10 hidden neurons.

The applied force-spectra F_z for all 1001 datasets are shown in Figure 5 (a). Amplitudes vary between a baseline amplitude of 0.01 N and a maximum peak amplitude of 0.2 N. The 2-dimensional diagram in Figure 5 (b) shows the excitation from dataset 512 more in detail. The connector distance for this specific configuration is 130 mm. Analogously to the excitation, the FEM-response a_z for all datasets (Figure 5 (c)) and in detail for dataset 512 (Figure 5 (d)) is shown. High amplitudes can be observed for 451 Hz, 991 Hz and 1441 Hz. As

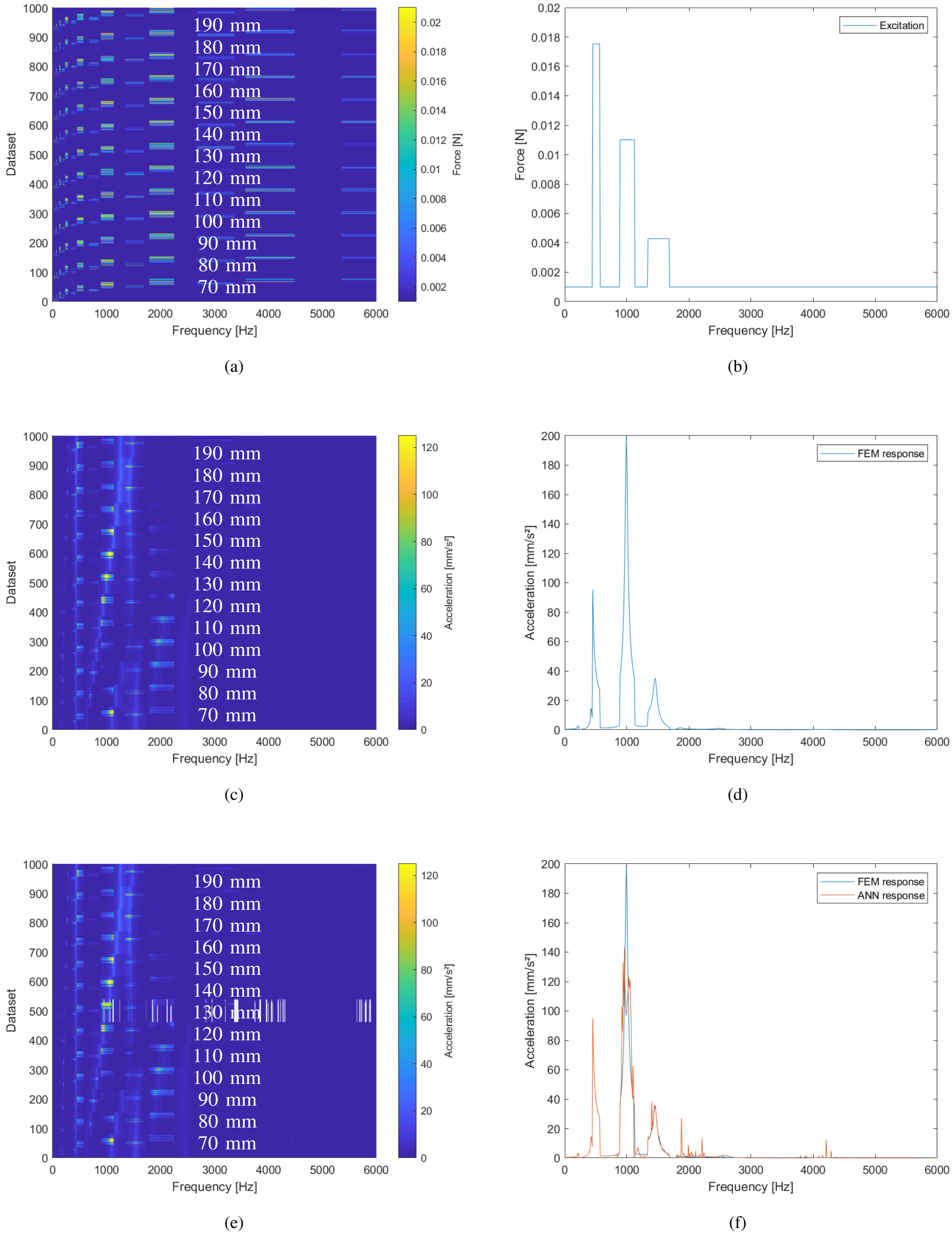

Figure 5. (a) Applied excitation for all structural configurations and force amplitudes. Increase of the x-value after each 77 datasets. (b) Force spectrum of dataset 512 which is related to a x-value of 130 mm. (c) Calculated FEM-response for all structural configurations and force amplitudes. (d) Acceleration spectrum of dataset 512 which is related to a x-value of 130 mm. (e) ANN response spectrum for all datasets. (f) Comparison FEM-response and ANN-response for dataset 512.

already mentioned, the FEM-data serves as artificially generated input in order to train Neural Networks that are capable of predicting transfer functions. The training was conducted with all datasets except those, representing a connector distance of 130 mm. This validation data is used to test the trained system of networks in terms of its capability of learning the relation between varying geometry and noise transfer function. As backpropagation, a bayesian regularization performs a minimization of a linear combination of squared errors and weights [3]. After training the networks, the excitations from Figure 5 (a) have been processed by the ANN-system which results in the response in Figure 5 (e). The general response is quite accurate, even though we see some deviating amplitudes for a x-value of 130 mm between 3000 and 4500 Hz. Prediction errors seem to concentrate in areas in which the input dataset consists of few amplitudes that vary from the baseline. The ANN-response of dataset 512 in Figure 5 (f) shows comparable amplitudes to the FEM-response for the peak values at 451 Hz and 1441 Hz. On the other hand, the amplitude at 991 Hz differs.

4 CONCLUSION

In this article we illustrated that Artificial Neural Networks are capable of predicting the system response for a noise transfer problem. These dynamics of the receiver are calculated as a function of force-excitation and geometry. The training data was artificially generated by utilizing FE-computations. In total 1001 input-force-spectra have been processed to receive a labeled output dataset for the ANN training and validation. The ANNs are able to respond to unseen geometrical configurations and excitations. The quantity of labeled data that represents a specific transfer function correlates with the accuracy of the prediction. For further verification, a larger database should be investigated.

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