Contribution analysis of road noise with transfer path analysis based on neural network

Uyeup Park¹
Mechanical Engineering/Institute of Advanced Machines and Design, Seoul National University 1, Gwanak-ro, Gwanak-gu, Seoul 08826, South Korea

Yeon June Kang²
Mechanical Engineering/Institute of Advanced Machines and Design, Seoul National University 1, Gwanak-ro, Gwanak-gu, Seoul 08826, South Korea

ABSTRACT
This paper introduces a new approach for transfer path analysis (TPA) based on a neural network. Various operating conditions were considered to obtain extensive operational data for training the neural network model, and long-term time domain data were converted into complex-valued frequency domain data according to the acquisition block. The numbers of layers and nodes of the model were determined by considering the physical characteristics of the system, and hyperparameters, such as the learning rate and momentum, were adjusted to improve convergence and efficiency. The reliability of the model was verified by comparing its estimated contribution and transmissibility with those obtained using existing methods. Unlike existing TPA methods, the neural network-based TPA method only requires operational data; furthermore, the proposed method reduces the cost of measurement step, such as impact tests, for identifying the propagation paths of noise.

1. INTRODUCTION

Transfer path analysis (TPA) is a method for evaluating the noise contribution of paths. It is possible to efficiently identify the cause of acoustic amplification in vehicle road noise. TPA is classified into three types classical TPA, component-based TPA and transmissibility-based TPA [1]. All types were developed based on multi-input and multi-output technique, using acceleration and sound pressure data. The classical TPA of structural-borne noise is used for calculating the force at the interface using acceleration data and estimating the sound pressure of each path; however, it requires measuring the frequency response function (FRF) of a passive system. The measurement of the FRF is time consuming because the system must be separated into subsystems. Many studies are being conducted to address the shortcomings of classical TPA; these involve component-based TPA, which measures the FRF in assembled system, and operational TPA, which uses only operating data [2, 3]. TPA research using neural networks is being actively conducted. Lee used an FEM model comprising a frame with a substructure for training the model and identified the main transfer path of the structure [4]. Tsokaktsidis measured training data through various operating scenarios and described noise transfer path in a full-vehicle context [5].

¹ dnduq5065@snu.ac.kr
² yeonjune@snu.ac.kr
In this study, a novel TPA method combined with a neural network technique that only uses operational data was developed. This study comprised two steps. The first step involved constructing a neural network model and obtaining datasets for training. To clarify the physical meaning of the parameters, a neural network model for TPA was constructed by selecting the activation function and number of nodes. Additionally, for model training, long-term measured time data were transformed into frequency domain data according to the acquisition block. The second step involved model training and result verification. The optimal weights that minimized the cost function can be derived by performing iterative calculations on many acceleration and sound pressure datasets. These weights allowed us to derive the transmissibility and noise contribution of each path of the vehicle suspension system. The reliability of the proposed method was verified by comparing its estimated noise contribution and transmissibility with those estimated by conventional TPA method.

2. THEORETICAL CONCEPTS

2.1. Transfer Path Analysis

TPA is used to identify the noise contribution of each path by measuring the noise path and vibration generated from an excitation source. This has become a major technique for troubleshooting noise, vibration, and harshness (NVH) problems in automotive engineering. The noise contribution of each path from the force acting at point m to the sound pressure at point o can be expressed as follows:

\[ P_{om}(\omega) = H_{om}(\omega) \cdot F_m(\omega) \]  

(1)

where \( P_{om} \) represents the sound pressure for each path, \( H_{om} \) represents the noise transfer function from the force acting point to the microphone, and \( F_m \) represents the complex force spectrum. The total sound pressure \( P_o \), is obtained as follows:

\[ P_o(\omega) = \sum_{m=1}^{M} P_{om}(\omega) = \sum_{m=1}^{M} H_{om}(\omega) \cdot F_m(\omega) \]  

(2)

The matrix inversion method is typically used for calculating force \( F_m \), which is obtained by multiplying the inverse inerance matrix \( H_{mn}^{-1} \) with structural response \( \ddot{x}_n \), as expressed in Equation 3. The transmissibility between sound pressure and acceleration can be derived using Equation 1 and 3; in Section 3, it is used as a reference to compare and verify the transmissibility derived using neural network model.

\[
\begin{pmatrix}
F_1 \\
\vdots \\
F_M
\end{pmatrix} = 
\begin{bmatrix}
H_{11} & \cdots & H_{1N} \\
\vdots & \ddots & \vdots \\
H_{M1} & \cdots & H_{MN}
\end{bmatrix}^{-1} 
\begin{pmatrix}
\ddot{x}_1 \\
\vdots \\
\ddot{x}_N
\end{pmatrix}
\]  

(3)

\[ P_{on}(\omega) = T_{on}(\omega) \cdot \ddot{x}_n(\omega) \]  

(4)

2.2. TPA based on a Neural Network

The neural network model, shown in Figure 1, takes structural response \( \{\ddot{x}_1, \cdots, \ddot{x}_N\} \) as input; calculates force \( \{F_1, \cdots, F_M\} \) in the \( r \)th hidden layer; and outputs the estimated sound pressure \( \{\ddot{p}_1, \cdots, \ddot{p}_0\} \). To obtain a physical result, the number of nodes in the input, output, and \( r \)th hidden
layers must be equal to N, O, and M, respectively. Furthermore, as TPA calculations are performed in the frequency domain, the neural network model must be constructed for each frequency line.

![Neural network model for TPA](image)

**Figure 1: Neural network model for TPA.**

The feed forward function of general neural network is expressed in Equation 5-7. Parameters such as weight \((W^1(\omega), \ldots, W^{R-1}(\omega))\) and bias \((b^1(\omega), \ldots, b^{R-1}(\omega))\) are updated during training to minimize the mean squared error function. The transmissibility between the input and output layers can be derived by calculating the weights and biases in all layers.

\[
Z^1(\omega) = W^1(\omega)\ddot{x}(\omega) + b^1(\omega)
\]

\[
a^1(\omega) = f(Z^1(\omega))
\]

\[
Z^{i+1}(\omega) = W^{i+1}(\omega)a^i + b^{i+1}(\omega) \quad (i = 1, \ldots, R - 1)
\]

\[
a^{i+1}(\omega) = f(Z^{i+1}(\omega))
\]

\[
\tilde{p} = a^R
\]

\[
\text{MSE} = \frac{1}{O} \sum_{o=1}^{O} (p_o(\omega) - \tilde{p}_o(\omega))^2
\]

However, unlike the general model, the neural network model for TPA can be applied in two different ways. First, the identity function should be used as the activation function because all values used in TPA are complex numbers, and the values calculated in the hidden layer should not be distorted by non-linear activation, such as sigmoid and ReLU. Second, all biases must be zero. As TPA is performed by multiplying the structural response with the inverted inerance matrix and noise transfer function, as expressed in Equations 1-4, it is not physically correct method to add any value to the output and hidden layers.

In neural network-based TPA, a large number of datasets are required for model training. In this study, to verify the neural network model, training and test datasets were collected using FEM. FEM can be used to easily obtain an accurate noise transfer function, an inerance matrix, and a large number of datasets. Figure 2 shows a box-car FEM model, comprising a frame and body, for simulating road noise. The random force, indicated by blue lines in the figure, is transmitted through the interface between the frame and body and transferred to the microphone marked by red circles. The random force components in the three-axis directions at the four points can be expressed as a complex vector, and many forces can be simulated by adjusting the amplitudes and phases of the 12 vector elements. In this study, the neural network model was trained using 3,000 datasets, and its transmissibility was verified (to be discussed in Section 3).
3. RESULTS

The sound pressure and noise contributions for each frequency were calculated using the updated weight and acceleration data. For result verification, classical TPA was selected as a reference and compared with the proposed model. Additionally, the proposed model was compared with a general model, and the difference were determined.

Figure 3(a) shows the validation loss results at 29 Hz. With increasing epoch, the loss converges to zero. Figure 3(b) shows a comparison between the target and estimated sound pressure levels for a certain scenario; clearly, the two graphs are consistent. However, as the main purpose of TPA is to derive the main transfer path and predict sound pressure, the noise contribution was calculated using these parameters.

Figure 4(a) shows the noise contribution results at 29 Hz, where White bars represent the reference TPA case, red bars represent the proposed neural network in this study, and blue bars represent the general neural network model case. It can be observed that the proposed neural network model is consistent with the reference result; however, errors occur when the general model is used. Figure 4(b) shows the synthesized vectors for each path for all cases. In all cases, the sum of the vectors indicates the same direction. The vector for each path of the proposed model is indistinguishable from that of the reference; however, there are many differences when the general model is used.

Figure 5 shows the results of transmissibility of the proposed neural network model is consistent with that of the reference. It was verified that the model could not only estimate the sound pressure but also derive the noise contribution for each path.

Figure 2: FEM model for training the neural network model.

Figure 3: Results of the neural network
(a): Epoch history of validation loss. (b): Estimated sound pressure level for a certain scenario.
4. CONCLUSIONS

Herein, a neural network model that considers physicality was presented. To obtain the training dataset for the model, random forces were applied at four positions in an FEM box-car model. Classical TPA was selected as the reference, and the results of the proposed and general models were compared. A neural network derives parameters using a training dataset and predicts the sound pressure when an arbitrary acceleration is input. Both the general and proposed models accurately estimated the sound pressure in the output layer. However, in terms of the noise contribution for each path, the results of the proposed model coincided with those of reference, but errors occurred when the general model was used. One reason is that the TPA is calculated by multiplying the FRFs; however, the values in the hidden layer are distorted when the biases are added to the hidden layer. Another reason is that when the non-linear activation function is applied to TPA, the values in the hidden layer change from negative to positive, and the phase information is distorted.

Unlike classical and component-based TPA, the proposed model uses only operating data; therefore, it is very efficient in terms of experimentation, such as FRF measurement. Automotive vehicle development processes are being continuously shortened. The proposed method for determining the main transfer path of noise can reduce the experimental cost in terms of NVH development.
5. ACKNOWLEDGEMENTS
The Institute of Engineering Research at Seoul National University provided research facilities for this work.

6. REFERENCES