4th Asia Pacific Conference of the Prognostics and Health Management,
Tokyo, Japan, September 11 – 14, 2023 OS07-02

Deep Learning Approach for Operational Transfer Path Analysis: Case Study of Electric Vehicles

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ABSTRACT

This paper presents a new approach to fault diagnosis of the drivetrains of the electric vehicle. Most commercially available electric vehicles do not have accelerometers on electric drivetrains making it difficult to detect fault characteristics of the drivetrains of the electric vehicle, whereas accelerometers exist on the driver's seat. The proposed approach's key idea is based on the operational transfer path analysis that determines the transfer function between the source and receiver. The transfer function is derived by training a deep learning model. The deep learning model converts the driver's seat vibration signals into drivetrains vibration signals. The validity of the proposed approach is evaluated using data from the durability test of real electric vehicles. It is anticipated that the proposed approach is effective to diagnose electric vehicle drivetrains subjected to external noise conditions.

1. INTRODUCTION

Electric vehicles are gaining popularity due to their eco-friendly nature and low operating costs. However, the drivetrains of electric vehicles is prone to failures, which can lead to decreased vehicle performance, increased maintenance costs, and even accidents. Therefore, fault diagnosis of electric vehicle drivetrains is crucial to ensure their safe and efficient operation. Vibration signal-based diagnosis has gained significant attention in recent years due to its high accuracy and reliability. Accelerometers are attached to various components of the electric vehicle to obtain vibration signals. For example, vibration signals from the driver's seat are mainly used to diagnose electric vehicle failures. However, accelerometers are not installed at the drivetrains of the electric vehicle. When the signals from the accelerometers at the driver's seat are used for fault diagnosis of drivetrains, they do not accurately represent the actual condition of the drivetrains since the accelerometers at the driver's seat are located far away from the drivetrains. To address the limitation, a proposed method uses a deep learning model based on operational transfer path analysis (OTPA). The deep learning model is used to convert the vibration signal from the driver's seat to the drivetrains vibration signal. This approach aims to enhance the fault feature of the vibration signal by converting from the driver seat to the drivetrains in an electric vehicle.

2. THEORETICAL BACKGROUND

The operational transfer path analysis (OTPA) is a technique that identifies and quantifies the paths through which vibration and noise are transferred from a source to a receiver (de Klerk & Ossipov, 2010). This method is commonly used to resolve noise, vibration, and harshness (NVH) problems in complex systems such as vehicles, aircraft, and industrial machinery. The technique involves measuring the vibration and noise at various points within the system and identifying transfer functions between the input (source) and output (receiver). OTPA can be used to determine the relative contributions of different components to the overall vibration levels, and to identify the most effective approaches for minimizing and eliminating unwanted vibration. The transfer function between the excitation source and the receiver can be modeled as:

$$\mathbf{X}(j\omega)\mathbf{H}(j\omega) = \mathbf{Y}(j\omega) \tag{1}$$

X is the excitation source signal; Y is the response signal; and H is the transfer function between the input and the output. Each component of the system is assumed to be linearly independent. To obtain the transfer function matrix, the inverse of the X matrix must be obtained. However, the X matrix is not always a square matrix. Therefore, an inverse matrix cannot be obtained. To solve this problem, the singular value decomposition (SVD) method is used. However, errors may still occur, especially in complex systems like automobiles where there is cross-talk between surrounding components, making it difficult to assume linear independence of each component.

3. Proposed Method

As discussed earlier, the signal of the receiver can be estimated by matrix multiplication of the source and the transfer function. In addition, it is possible to estimate the source signal by the inverse matrix calculation. However, the accuracy is poor due to the problems mentioned above. To overcome the challenges associated with the use of the traditional OTPA approach, this section proposes a deep-learning-based model that converts driver's seat signals to drivetrain signals. Deep learning excels at representing non-linear relationships between inputs and outputs.

The deep learning model for vibration signal conversion consists of two pairs of encoder and decoder combinations, as depicted in Figure 1. The first encoder-decoder combination represents a transfer function that defines the relationship between the driver's signal and the transition points signals, while the second combination defines the relationship between the transition points signals and the drivetrains signal.

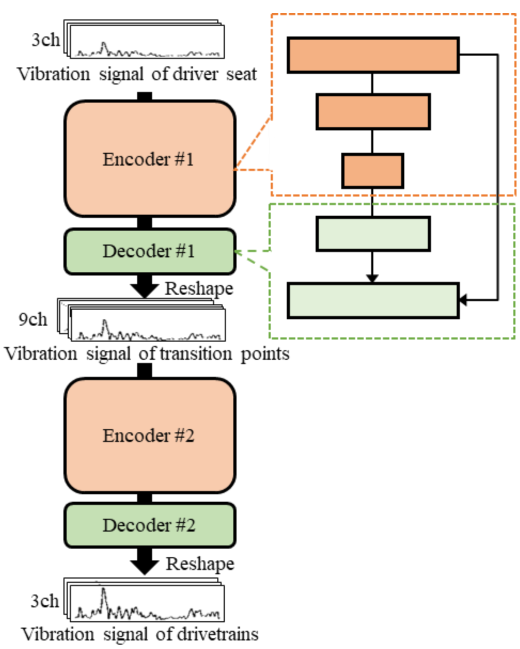


Figure 1. Deep learning model architecture for OTPA

Both the encoder and decoder consist of a fully connected layer. Input data with *n* dimensions are connected to nodes in the *m* dimensions with weights and linearly converted into the desired output.

The encoder gradually reduces the dimension of the data to extract the features of the vibration signal, and the decoder maps the extracted features to the vibration signal of the transition points and drivetrains. In this paper, a skip connection is used to improve the model's performance. Skip connection refers to a configuration that adds the previous layer input value as a residual to the output value of the later layer, unlike the existing forward path of the deep learning model. The implementation of skip connections to the model can effectively alleviate the problem of information loss and gradient vanishing in the initial layer that may occur in the deep learning model (He et al., 2016). In this study, the skip connection is configured to transfer the output from the first layer of the encoder to the input from the last layer of the decoder.

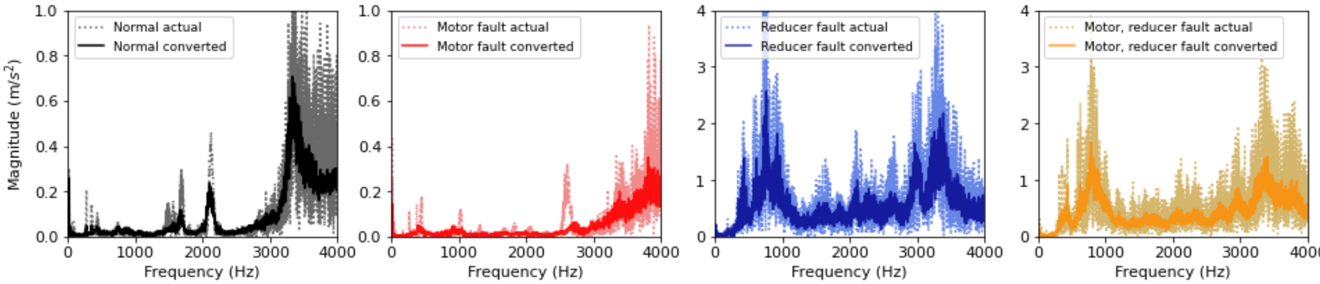
The existing OTPA method calculates the output signal using an individual transfer function for each frequency component (Cheng et al., 2020). Moreover, each measurement direction and point are calculated under the assumption of linear independence. However, this assumption may not be appropriate considering the nonlinear interaction between components in an electric vehicle in practice. In contrast, the proposed method integrally calculates the output by providing all frequency components. In addition, the deep learning model can learn the nonlinearity between each measurement direction and point using the activation function present in each layer.

4. Case Study

4.1. Experimental Setup

Vibration data were collected using an electric vehicle that was driven 298,000 km during a durability test. The experimental setup is presented in Table 1. The transition points on the electric vehicle body were selected in cooperation with test experts. The three-axis acceleration of x, y, and z was measured at a total of 72 channels with the sampling rate of 25,600 Hz. Additionally, the experiment was conducted with the identical setup parameters for the two main drive system components, the motor, and gearbox (reducer), which were mounted on the electric vehicle with four normal and defective parts, respectively. The data were collected during the driving under various constant-speed situations (30, 50, 80, and 100 km/h), as well as acceleration and deceleration driving scenarios (MTI and WOT) between 0 and 120 km/h.

This study used only the data from points identified as crucial for analyzing transfer paths by OTPA domain experts, rather than all data collected from the 72 channels.



(a) (b) (c) (d)

Figure 2. Representative examples of the converted signals and actual signals in drivetrains in MTI condition: (a) normal; (b) motor fault; (c) reducer fault; (d) motor and reducer fault

Table 1. Experimental setup

Measurement points		72 channels (Seat, motor, reducer, mounts, subframe, G-bush, knuckle, shock absorber, steering wheel)			
Sampling rate		25,600 Hz			
Sample	Motor	Faulty	Faulty	Normal	Normal
	Gearbox	Faulty	Normal	Faulty	Normal
Operational conditions		Stationary (30, 50, 80, 100 km/h), MTI, WOT			

Table 2. Comparison of errors for converting from driver seat signals to drivetrain signals

Metric	Location	Method	
		Proposed method	SVD
Averaged MAE (m/s^2)	Transition points	0.0044	0.0052
	Drivetrains	0.084	0.1255
R2 score	Transition points	0.53	0.32
	Drivetrains	0.45	-1.44

the motor served as the excitation source, the driver's seat as the receiver, and three locations composed of the intermediate transition points: the shock absorber mount, the subframe mount, and the motor/reducer mount. To convert the data, a window was chosen to include the data points from 25,600 vibration signals measured over one second. By dividing the data with a 70% overlapping ratio, the fast Fourier transform (FFT) was implemented. The resulting signal had the frequency resolution of 1 Hz in the frequency range of 0 Hz to 12,800 Hz. For this study, data were limited to frequencies ranging from 0 Hz to 4,000 Hz to reduce the dataset and model size.

The three-fold cross-validation was used to train and test the deep learning models for OTPA. For training, the loss was the summation of the L_1 loss functions at the transition points and the drivetrains. The activation function was ReLU (Rectified Linear Unit). The optimizer was Adam. The model has 150 learning epochs, 64 batches, and a learning rate of 0.0001.

The performance of the deep learning model for converting the driver's seat vibration signal was evaluated using the averaged MAE value and R2 score. The MAE value is the mean of the absolute error between the observed and predicted values. The R2 score is a metric of the adequacy of the regression model and represents the ratio of the variance of the estimated regression value to the variance of the actual value. The maximum R2 score value is 1, and the closer it is to 1, the better the correlation between the regression model and the actual data. The model's results were compared to those of the existing SVD-based.

4.2. Results

This paper proposes a deep-learning-based method to convert vibration signals and evaluates their consistency with actual vibration signals through visual inspection. As a representative example, the vibration signals obtained under the MTI operating condition at a particular time for each failure mode are presented in Figure 2. Visual inspection reveals that the converted vibration signal effectively predicts the overall trend of the actual vibration signal.

To evaluate the performance of the proposed method, Table 2 shows the results of converting the driver's vibration signals using both the proposed deep learning-based method and the existing SVD-based method. The proposed method resulted in a lower MAE value of 0.0044 m/s^2 at the vehicle transition point and 0.084 m/s^2 in the drivetrains compared to the existing method's MAE of 0.0052 m/s^2 and 0.1255 m/s^2, respectively. In both the transition point and the drivetrains, the proposed method outperforms the existing method in both MAE and R2 score comparisons. Thus, the results indicate that the proposed method exhibits excellent performance.

5. CONCLUSION

To address the issue of the unavailability of vibration data from the drivetrains of electric vehicles, this study incorporated the concept of OTPA innovatively. The deep learning model performs OTPA by utilizing data from critical transfer path points of the electric vehicle. As a result, the vibration signal of the drivetrains is estimated based on the vibration signal obtained from the driver's seat. The proposed method eliminates the necessity of attaching an accelerometer to the drivetrains of the electric vehicle. It is expected that the vibration signal from the driver's seat can be used to diagnose faults in the electric vehicle drivetrains with high accuracy.

ACKNOWLEDGMENT

This work was supported by the Hyundai Motor Company and the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2021R1A2C1008143).

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BIOGRAPHIES

Jeongmin Oh received the B.S. degree in mechanical design engineering from Pukyong National University, Busan, Republic of Korea, in 2022, where he is currently pursuing the M.S. degree in mechanical engineering. His current research topics include prognostics and health management for rotating machines.

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