Fault Diagnosis of Multiple Components in Complex Mechanical System Using Remote Sensor

Jeongmin Oh[1], Hyunseok Oh[2], Yong Hyun Ryu[3], Kyung-Woo Lee[4], and Dae-Un Sung[5]

[1,2] *School of Mechanical Engineering, Gwangju Institute of Science and Technology, Gwangju, 61005, Republic of Korea*
jmoh1010@gm.gist.ac.kr
hsoh@gist.ac.kr

[3,4,5] *Vehicle Performance Degradation Research Laboratory, R&D Center, Hyundai Motor Company, Hwaseong, 18280, Republic of Korea*
skidmarker@hyundai.com
caselee@hyundai.com
dusung@hyundai.com

ABSTRACT

This study proposes an approach to monitor multiple components in complex mechanical systems using a single, externally placed remote sensor. In automobiles and petrochemical plants, where numerous components (e.g., powertrain, bearing, and gear), sensor placement is often compromised by cost and installation environment constraints, resulting in sensing the components far from the regions of interest. To address this challenge, this paper proposes an Operational Transfer Path Analysis (OTPA)-based approach that derives the transfer functions between the vibration excitation source and the measurement point (i.e., receiver). The model for OTPA enables the reverse estimation of the excitation source's signal from the receiver. Subsequently, the estimated (i.e., synthesized) source signal is fed into a diagnostic model to identify system faults. The OTPA and diagnostic models are constructed using neural network architectures, enabling better adaptation to operational conditions and system-induced nonlinearities. The proposed approach is validated from case studies using hydraulic piston pumps in construction vehicles and next-generation electric vehicles.

1. INTRODUCTION

Rotating machine components inevitably produce vibrations during operation, which sensitively reflect the health condition of the rotating machines. Hence, vibration data is predominantly used for fault diagnosis. Such data is often complex and high-dimensional, making effective analysis challenging. Several years ago, deep learning-based approaches were proposed for fault diagnosis in rotating machines. For instance, Zhao, Yan, Chen, Mao, Wang, and Gao (2019) significantly improved the accuracy of motor fault diagnosis using Convolutional Neural Networks (CNN). Their research demonstrates that CNN can successfully classify complex vibration patterns and detect early signs of faults in motors. Additionally, Chen, Zhang, Cao, and Wang (2020) utilized one-dimensional Nonlinear Output Frequency Response Functions and Stacked Denoising Auto-Encoders (SDAE) for diagnosing faults in Permanent Magnet Synchronous Motors (PMSM). The superiority of the proposed method was validated using data from simulations of nonlinear systems such as PMSMs in passenger vehicles.

The existing methods discussed above input data captured from sensors attached to key rotating components such as motors and bearings into deep-learning models for fault diagnosis. Such approaches are effective when sensors can be installed at fault-sensitive points of the rotating machines. In the testbed of the rotating machines, multiple sensors can be attached at various points to diagnose rotating machines effectively using collected vibration data. However, in most operating rotating machines, vibrations arise from numerous rotating parts, and installing sensors at each potential vibration point is often impractical due to cost and environmental constraints. If it is possible to diagnose health conditions using a single sensor installed far from the vibration source, it could significantly reduce costs for data acquisition. Upon further literature review, several innovative studies were found. Choudhary, Mian, Fatima, and Panigrahi (2022) and Yao, Liu, Song, Zhang, and Jiang (2021) creatively proposed diagnosing rotating machines using non-invasive acoustic sensors. Even while acoustic sensors have the amazing benefit of being able to detect signals over long distances, their susceptibility to external noise can make them inappropriate for use in particular machines such as passenger vehicles.

This paper proposes a novel approach to address two challenges: (1) difficulty in installing vibration sensors on various rotating components within rotating machines, and (2) reduced signal sensitivity and increased interference from external noise when using vibration signals measured at external points. Through Operational Transfer Path Analysis (OTPA), the vibration signal measured at an external point is converted into a vibration signal from the core vibration source, and faults are diagnosed using a denoising deep learning model.

The remainder of this paper is organized as follows: Section 2 describes the OTPA concept, which forms the theoretical background of this paper. Section 3 discusses the proposed approach. Section 4 presents two case studies using a hydraulic pump in a construction vehicle (CV) and a drivetrain of an electric vehicle to verify the proposed approach. Finally, Section 5 summarizes the content of this paper.

2. Theoretical Background

OTPA is a technique that identifies and quantifies the paths through which vibration and noise are transferred from a source to a receiver (van der Seijs, de Klerk, and Rixen, 2016). Within rotating machines, the input excitation source and the output receiving point can be represented as shown in Figure 1. The relationship between the input excitation source and the output receiving point can be modeled by Frequency Response Function (FRF) as in Eq. (1). through which the response at the receiving point due to an input at the excitation source can be calculated.

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

The transfer function is formulated as:

$$\begin{bmatrix} x_1^{(1)} & \cdots & x_1^{(M)} \\ \vdots & \ddots & \vdots \\ x_r^{(1)} & \cdots & x_r^{(M)} \end{bmatrix} \begin{bmatrix} H_{11} & \cdots & H_{1N} \\ \vdots & \ddots & \vdots \\ H_{M1} & \cdots & H_{MN} \end{bmatrix} = \begin{bmatrix} y_1^{(1)} & \cdots & y_1^{(N)} \\ \vdots & \ddots & \vdots \\ y_r^{(1)} & \cdots & y_r^{(N)} \end{bmatrix} \tag{2}$$

where r represents the total count of data sets collected for each point during operation.

In the process of delineating the transfer function matrix, it is imperative to compute the inverse of the matrix X. However, typically, the matrix X is not a square matrix, its inverse matrix cannot be calculated. To overcome this limitation, the Singular Value Decomposition (SVD) technique is employed (Cheng, Zhu, Chen, Song, Zhang, Gao, Liu, Nie, Cao, and Yang, 2022). SVD enables the decomposition of the matrix X as shown in Eq. (3).

$$\mathbf{X} = \mathbf{U\Sigma V}^{\mathrm{T}} \tag{3}$$

where U signifies the unitary matrix; Σ denotes the diagonal matrix constituted by singular values; and V^T represents the conjugate transpose of the unitary matrix V. Through Eq. (3), it is feasible to obtain the pseudo-inverse of matrix X, a process equivalently captured in Eq. (4).

$$\mathbf{X}^{+} = \mathbf{V\Sigma}^{-1}\mathbf{U}^{\mathrm{T}} \tag{4}$$

Subsequently, the formulation of the transfer function is articulated as:

$$\tilde{\mathbf{H}} = \mathbf{X}^{+}\mathbf{Y} \tag{5}$$

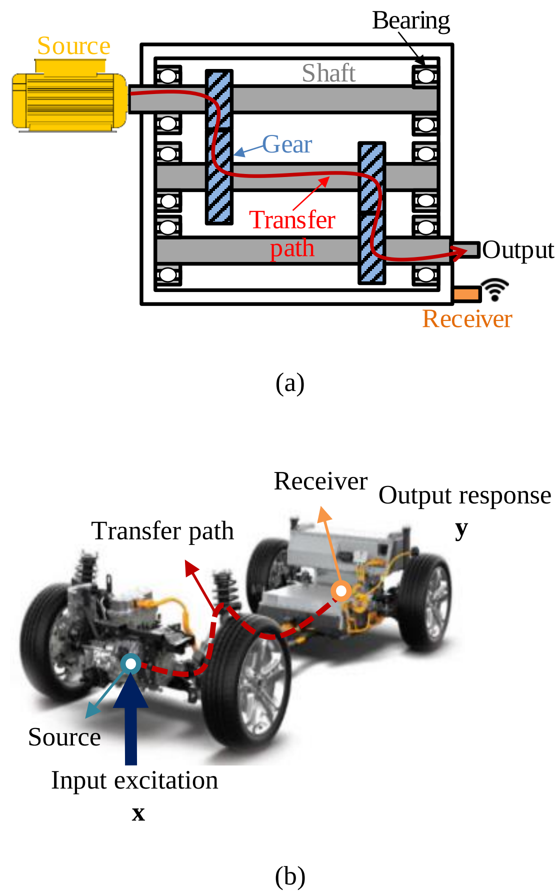


Figure 1. Scheme of the transfer path: (a) gearbox, (b) electric vehicle chassis.

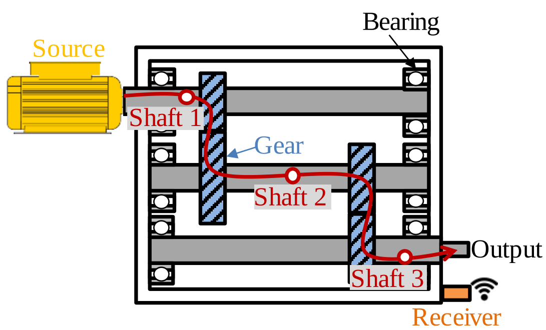
3. Methodology

This section presents the proposed approach in this paper. Section 3.1 elaborates on the selection of critical points within rotating machines for vibration signal acquisition and the preprocessing of these signals for the OTPA model. Section 3.2 discusses the architecture of the OTPA model, which transforms measured vibration signals at the receiver into the source vibration signals, and the architecture of the fault diagnosis model that inputs the synthesized vibration signals. Finally, Section 3.3 describes the training procedure of the models and the metrics employed for performance evaluation.

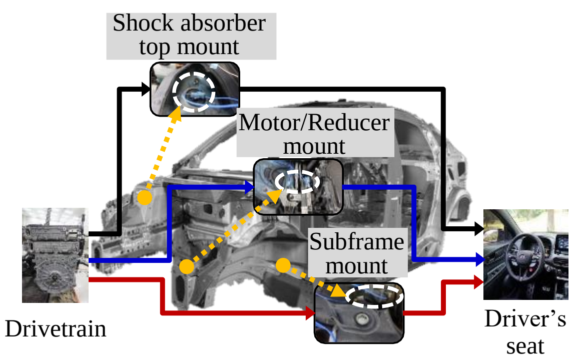
3.1. Data Acquisition and Signal Preprocessing

For the deployment of the OTPA model, initial steps involve the identification of crucial data acquisition points. For instance, in a standard gearbox scenario, sources can be designated as the motor, the receiver as the output case, and transition locations as shafts 1, 2, and 3, as depicted in Figure 2(a). Similarly, for electric vehicles (EVs), the source (excitation point) is determined as the motor, the receiver as the driver's seat, and transition points include the shock absorber mount, subframe mount, and motor/reducer mount, illustrated in Figure 2(b).

Subsequently, acquired vibration signals are converted into frequency spectra using the Fast Fourier Transform (FFT). To mitigate discontinuity issues stemming from finite signal length, a Hanning window is utilized. The overlap rate is 50 %.



(a)



(b)

Figure 2. Source, receiver, and transition locations: (a) CV gearbox, (b) EV chassis.

3.2. Model Building

The proposed model framework, as shown in Figure 3, is comprised of an OTPA deep learning model and a drivetrain fault diagnosis deep learning model. The OTPA deep learning model features two serially connected pairs of a feature extractor and a regressor. The initial OTPA module pair aims to model the transfer function relationship between the receiver signals and those of the transition locations. The subsequent pair focuses on modeling the transfer function relationship between the transition location signals and the excitation source signals.

Feature extractors are composed of 1D convolutional layers, with subsequent regressors mapping the extracted features to vibration signals at transition locations and the drivetrain. Signals measured at the receiver, upon traversing the first feature extractor and regressor combination, are transformed into vibration signals at transition locations; these are then converted into drivetrain vibration signals via the second combination. The final loss function, as represented in Eq. (6), summation of the L_1 losses at transition locations and the drivetrain.

$$L_{total} = L_{trans} + L_{source} \tag{6}$$

where L_{trans} represents the loss at transition locations; and L_{source} denotes the loss at the excitation source. The proposed deep learning model is trained to minimize the combined loss of transition and excitation source locations.

The difference between the proposed deep-learning-based OTPA and conventional OTPA methods lies in the feature extractor. Traditional OTPA methods calculate output signals for specific input signal frequency components using transfer functions, assuming linear independence among measurement directions and locations (de Klerk & Ossipov, 2010). However, such assumptions do not hold when nonlinear interactions within rotating machine components exist. Conversely, the proposed method integrates all frequency components as a singular input to the feature extractor for overall output calculation. Furthermore, the feature extractor leverages activation functions within each layer to learn the nonlinearities between measurement directions and locations. Significantly, 1D convolutional layers facilitate the learning of local band-specific features within the frequency domain, an advantage under variable speed conditions common in rotating machines.

The preprocessing stage involves augmenting the receiver vibration signals with Gaussian noise of varying intensities, creating a dataset with a broad range of signal-to-noise ratios for deep learning model training. While the input data for model training incorporate noise-enhanced signals, the output data utilize the original, unaltered vibration signals. The objective is to train the deep learning model on input data variability, thus ensuring signal transformation accuracy against external noise influences. This approach anticipates effective vibration signal conversion even in harsh operational conditions characterized by significant external noise.

The deep learning model for fault diagnosis employs a conventional Multi-layer Perceptron (MLP) architecture. Input data consist of triaxial (x, y, z) drivetrain frequency domain vibration signals. Parallel-configured MLPs for each channel extract data features, which after layer normalization, are concatenated. The combined features traverse another MLP layer, ultimately outputting indices pertaining to fault types.

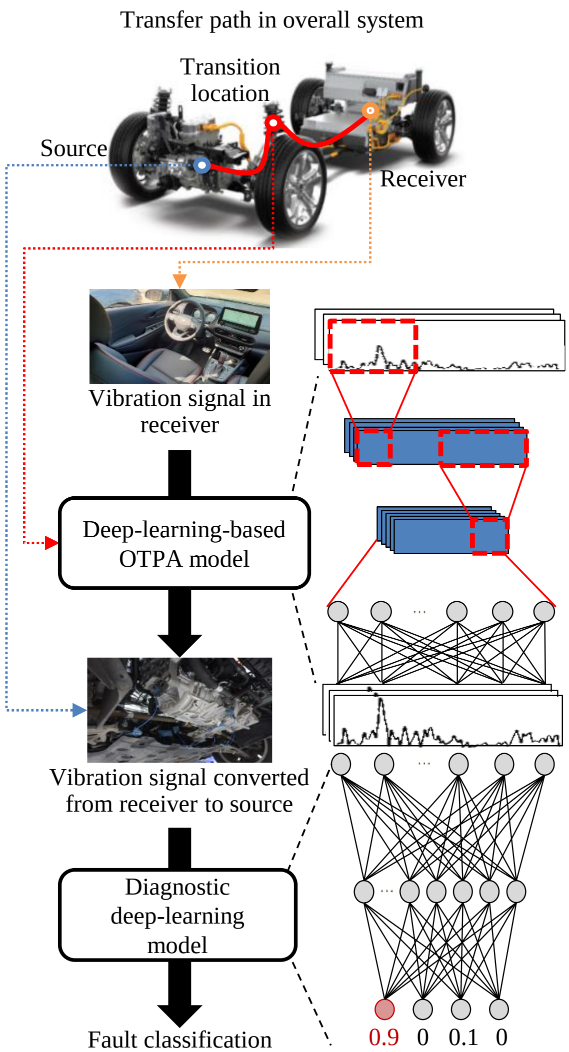


Figure 3. Model construction in the proposed approach.

3.3. Model Training and Performance Evaluation

The synthesized source vibration signals from the deep-learning-based OTPA model are inputted into a trained fault diagnosis deep learning model for assessing the rotating machines' condition. Activation functions across layers in both the OTPA and fault diagnosis models utilize the Rectified Linear Unit (ReLU), with loss functions employing L1 and cross-entropy functions, respectively. The optimizer of choice is Adam.

To objectively evaluate the deep learning models' performance, k-fold cross-validation is conducted. The Mean Absolute Error (MAE) metric assesses the regression fit of the OTPA model. Additionally, accurately realizing local band amplitude fluctuations in the synthesized vibration spectrum, akin to the measured spectrum, is crucial. This aspect can be assessed through variance, thus employing the correlation coefficient as an auxiliary performance metric.

4. EXPERIMENTS

4.1. Case I: Hydraulic Piston Pump

Hydraulic piston pumps are integral in various industries such as construction, maritime, and mining for energy conversion processes. Compared to electric vehicle systems, hydraulic piston pump systems usually have shorter distances between the excitation source and the receiver, resulting in less variance due to external noise. This study investigates the denoising efficacy of the proposed method by artificially introducing external noise to vibration signals obtained at the receiver.

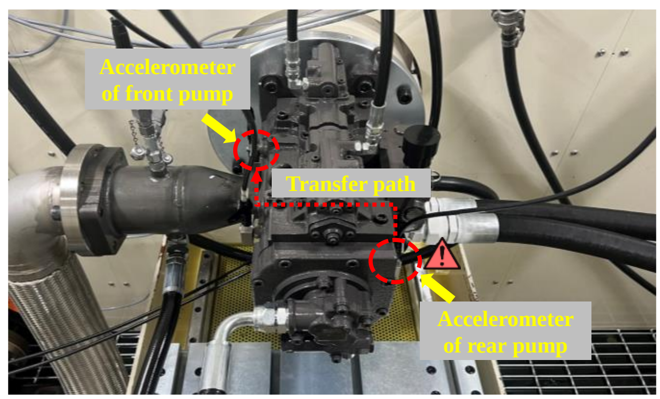


Figure 4. Hydraulic piston pump testbed, measurement points, and transfer path.

4.1.1. Overview

A hydraulic piston pump used in a 22-ton excavator was selected as the subject of our test bed, depicted in **Error! Reference source not found.**. The pump operates at 1800 rpm with a discharge pressure maintained at 350 bar. It is equipped with an axial piston pump at both the front and rear, forming a pair. Artificial defects were introduced into the rear pump piston.

The primary failure modes of axial piston pumps are known to be surface wear between the piston and slipper. Wear occurs due to the chemical degradation of internal lubricants, potentially leading to piston detachment from the slipper, ultimately damaging the piston pump. Based on an understanding of these failure origins, mechanisms, and modes, piston surface defects were simulated by artificially altering the piston surface tolerances, thereby mimicking increased part tolerances. Tolerances ranging from 0 to 15 μm were classified as normal, 90 to 120 μm as partially-degraded, and 120 to 150 μm as severely-degraded.

Assuming the front pump as the receiver and the rear pump as the excitation source (i.e., the location of fault occurrence), it was hypothesized that utilizing the synthesized vibration signal from the front to the rear pump for diagnosis could achieve higher accuracy. This is because the front pump, physically distant from the actual fault-occurring rear pump, acquires vibration signals that are more susceptible to external noise and contain attenuated signals from the rear pump.

Table 1. Experimental setup for hydraulic piston pump testbed.

Operation condition	1800 rpm
Load condition	350 bar
Oil temperature	50 °C
Number of samples	3 EA
Fault condition (Clearance)	Normal (0~15 μm) Rear partially-degraded (90~120 μm) Rear severely-degraded (120~150 μm)
Sampling rate	10,240 Hz
Measurement points	6 channels (Rear, front x, y, z axis)
Acquisition time	900 sec

Table 2. Train and test dataset configuration for case I.

Training	Original, SNR 20, 10, 0 dB
Test	Original, SNR 20, 15, 10, 5, 0, -5, -10 dB

4.1.2. Data Acquisition and Signal Preprocessing

Vibration data were collected under the conditions detailed in **Error! Reference source not found.** using triaxial accelerometers mounted on the axial piston pump. As described in Section 3.1, the acquired signals were preprocessed and converted into frequency spectra using FFT. A Hanning window of 10,240 data points was used without overlap between consecutive windows. The frequency domain of the transformed vibration signals ranged from 0 Hz to 5,120 Hz. For data set efficiency, frequency domains from 0 Hz to 1,280 Hz were utilized.

To simulate environments with greater distances between vibration acquisition points and more susceptibility to external noise than the hydraulic piston pump samples used in this study, data was augmented by adding Gaussian noise to the assumed receiver signal (front signal), thereby decreasing the SNR as detailed in **Error! Reference source not found.**.

4.1.3. Model Construction and Training

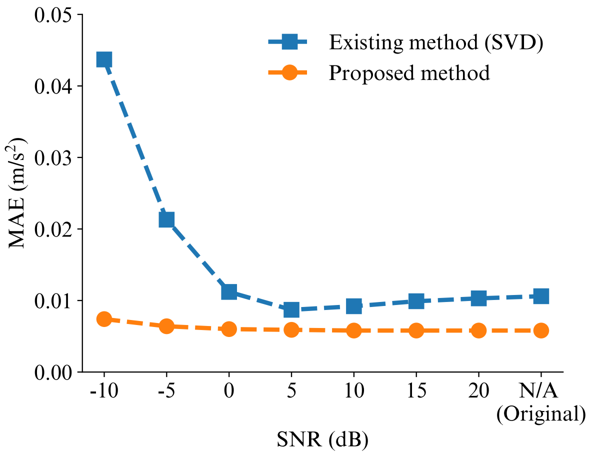
The architecture of the OTPA deep learning model consists of 1D CNN and FC layers, incorporating feature extractors and regressors. Input data comprise frequency spectra of triaxial vibration signals measured at the front pump, while output data consist of the rear pump's triaxial vibration signal spectra. Hyperparameter optimization, conducted empirically, set training epochs at 150, batch size at 64, and learning rate at 0.0001.

For the fault diagnosis deep learning model, the inputs consist of three-channel excited source spectra with 1,280 data points. Outputs predict the fault vector. Hyperparameter optimization resulted in setting training epochs at 50, batch size at 64, and learning rate at 0.0001. This case study implemented a five-fold cross-validation.

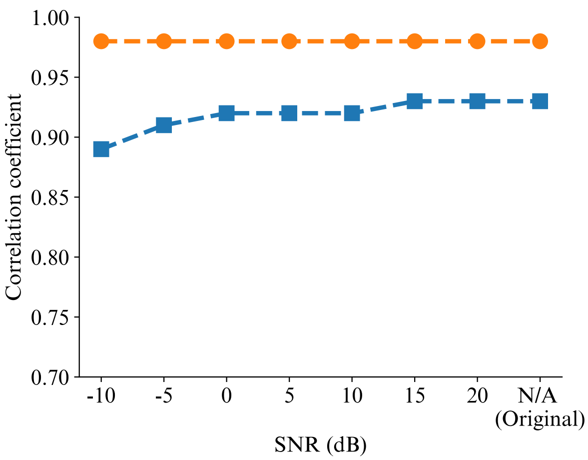
4.1.4. Results

Vibration signal synthesizing results are presented in Figure 5. Using the conventional SVD-based OTPA method, MAE values of 0.0106 m/s² for the original test dataset and 0.0437 m/s² for the dataset with the lowest SNR of -10 dB were observed. In contrast, the proposed method yielded MAE values of 0.0057 m/s² for the original dataset and 0.0070 m/s² for the -10 dB SNR dataset, demonstrating superior performance across all SNR datasets compared to the existing method. Notably, despite all methods showing increasing error trends with higher noise levels, the proposed method exhibited significantly lowered error growth rates, indicating its robustness against noise. Correlation coefficient comparisons also affirmed the superior performance of the proposed method, highlighting the effectiveness of the proposed deep learning-based vibration signal synthesizing method.

Piston fault diagnosis outcomes, comparing front signals to synthesized rear pump signals, are illustrated in Figure 6. Diagnosis performance using front signals was evaluated based on models trained on identical front signals, whereas diagnosis with synthesized rear signals was based on models trained on actual rear signals. Up to SNR 20 dB, both front and synthesized rear signals demonstrated near-perfect diagnostic accuracy. However, as noise levels increased, the diagnostic accuracy based on front signals declined sharply, whereas the accuracy based on synthesized signals remained relatively stable. Notably, for datasets not included in the training process with SNR of -10 dB, front signals showed the diagnostic accuracy of 38.59%, while synthesized signals achieved a significant difference of up to 89.08%. This indicates that, in noisy environments, inputting synthesized signals from the front to the rear pump enables better differentiation of piston defects, demonstrating the OTPA model's effectiveness in denoising.



(a)



(b)

Figure 5. Performance comparison of the proposed with existing methods for vibration signal conversion: (a) Maximum absolute error and (b) Correlation coefficient.

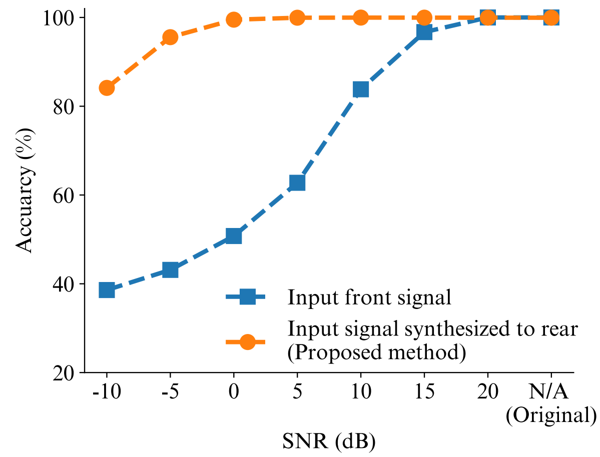


Figure 6. Accuracy comparison of the proposed and existing methods in fault diagnosis.

Table 3. Experimental setup for electric vehicles.

OTPA setup	Sources: electric motor, gearbox Transitions: mounts, subframe, G-bush, knuckle, shock absorber Receiver: driver's seat
Driving conditions	Constant speed of 30, 50, 80, 100 km/h Full acceleration from 0 to 120 km/h with wide open throttle (WOT) 50% acceleration from 0 to 120 km/h with middle tip in (MTI)
Measurements	Sampling rate: 25,600 Hz Data acquisition duration: 25~65 seconds

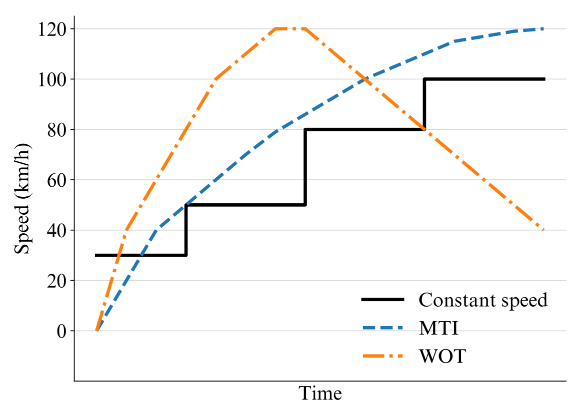


Figure 7. Driving speed profiles.

4.2. Case II: Electric Vehicle Drivetrain

This case study sought to validate the efficacy of the proposed method by implementing it to EVs in the field, synthesizing vibration signals acquired from the driver's seat into drivetrain signals for fault diagnosis. This section consists of subsections including data acquisition and signal preprocessing, model building, training, and performance evaluation, and results.

4.2.1. Data Acquisition and Signal Preprocessing

Vibration data from an electric vehicle, having completed approximately 300,000 km of operation, were collected. Experimental conditions are detailed in **Error! Reference source not found.**. Using a triaxial accelerometer (DYTRAN 3093M4) with the sampling rate of 25,600 Hz, data were acquired from key components within the EV chassis. The EV drivetrains, comprising motor and gearbox components, were prepared by installing faulty or healthy components to simulate different health condition combinations. Data collection covered various driving conditions, including constant speeds of 30, 50, 80, 100 km/h, and dynamic acceleration-deceleration cycles (Wide Open Throttle; WOT and Middle Tip In; MTI), as illustrated in **Error! Reference source not found.**.

Following the methodology outlined in Section 3.1, collected vibration signals underwent preprocessing before being transformed into frequency spectra using the Hanning window of 25,600 data points and the 50% overlap between consecutive windows. The frequency range of the transformed signals was from 0 to 12,800 Hz. The data from 0 to 4,000 Hz deemed most informative for the dataset.

4.2.2. Model Building, Training and Performance Evaluation

The input to the OTPA deep-learning model consisted of triaxial vibration spectrum data acquired from the driver's seat. These signals were processed through first feature extractor and regressor to convert them into transition locations vibration signals, which were then further converted (or synthesized) into drivetrain vibration signals via second feature extractor and regressor. After optimizing hyperparameters, the training epochs was 150; the batch size was 64; and the learning rate was 0.0001. Performance evaluation of the OTPA model was segmented into constant speeds, acceleration, deceleration, and overall conditions.

The drivetrain fault diagnostic deep-learning model followed the same approach as described in the previous case study. Inputs were the frequency spectra of the converted drivetrain signals, with outputs categorizing into four classes: "normal," "faulty motor," "faulty reducer," and "faulty motor and reducer." After optimizing hyperparameters for the drivetrain fault diagnosis model, the training epochs were 50; the batch size was 64; and the learning rate was 0.0001. The EV drivetrain fault diagnosis model's performance was evaluated under interpolation and extrapolation conditions. In the interpolation condition, models were trained using datasets encompassing all three driving profiles (constant speeds, WOT, MTI), then tested on the same driving conditions. For extrapolation, models were trained exclusively on WOT datasets and tested on constant speeds and MTI datasets not used during training. A three-fold cross-validation was conducted for this case study.

Table 4. Performance evaluation of OTPA models in case of EV.

Transfer path	Driving speed profile	Mean absolute error (dB)		Correlation coefficient	
		Proposed method	SVD	Proposed method	SVD
From driver's seat to transition locations	Constant speed	5.58	6.17	0.77	0.73
	WOT	5.84	6.22	0.67	0.66
	MTI	5.81	6.31	0.70	0.67
	Average (=A)	5.67	6.21	0.74	0.70
From transition locations to drivetrains	Constant speed	5.47	10.25	0.70	0.37
	WOT	6.60	9.16	0.63	0.39
	MTI	6.24	9.89	0.64	0.31
	Average (=B)	5.80	10.02	0.68	0.36
From driver's seat to drivetrains	Total (= A + B)	11.47	16.23	1.42	1.06

4.2.3. Results

The performance of the proposed models was presented in **Error! Reference source not found.**. The proposed model showed the MAE of 11.47 dB and the sum of correlation coefficients of 1.42. The conventional SVD model showed the MAE value of 16.23 dB, significantly higher by 41.4% compared to the proposed model. The sum of correlation coefficients was 25.4% lower at 1.06 than the proposed model. This underscores the superior performance of the proposed model in the operational transfer path analysis.

Subsequent fault diagnosis using the synthesized signals was performed. The performance of the drivetrain fault diagnostic deep-learning model was divided into interpolation and extrapolation conditions for evaluation. The drivetrain fault diagnostic results for each input signal are summarized in Table 5. Interpolation performance showed nearly 100% diagnostic accuracy for both actual driver's seat and drivetrain signals, and similarly high accuracy for signals synthesized via the proposed methods. However, the conventional SVD approach showed a slight decline to 95.60% accuracy when performing OTPA under varying operational and condition settings (multiple SVDs), and a significant decrease to 34.83% when a single model approach (single SVD) was applied across all conditions.

For extrapolation, the driver's seat signals exhibited a diagnostic accuracy of 90.38%, and drivetrain signals showed 99.32% accuracy. This indicates that the diagnostic model distinguishes drivetrain fault modes more effectively when drivetrain signals are inputted under new driving conditions than when driver's seat signals are used. Additionally, synthesized drivetrain signals, excluding the conventional SVD method, also demonstrated nearly 100% accuracy, similar to actual drivetrain signals. This indicates that the synthesized signals accurately reflect the fault characteristics of actual drivetrain signals, suggesting the effectiveness of the proposed method in accurately diagnosing faults in electric vehicle drivetrains under various operational conditions.

Table 5. Fault diagnostic performance evaluation.

Input	Accuracy (%)	
	Interpolation	Extrapolation
Actual signal measured at driver's seat	99.96	90.38
Actual signal measured at drivetrain	99.98	99.32
Synthesized signal by Single SVD	34.38	33.65
Synthesized signal by multiple SVDs	95.60	93.60
Synthesized signal by proposed method	99.92	99.31

5. Conclusion

This paper presented an approach based on Operational Transfer Path Analysis (OTPA) deep-learning modeling for diagnosing faults in rotating machines. The proposed method aimed to address two primary challenges: (1) the absence of vibration sensors at the excited source and transition locations in rotating machines, and (2) the reduction in signal sensitivity due to external noise interference when utilizing vibration signals measured at the receiver. Initially, the transfer paths between the noise generation point (source), transition locations, and the sensor acquisition point (receiver) were defined. Subsequently, a denoising deep-learning model was proposed based on the OTPA concept to capture the nonlinear relationships between the frequency spectra of the excited source, transition locations, and the receiver. To validate the effectiveness of the proposed approach, two case studies were conducted. The case study involving a hydraulic piston pump in construction vehicles demonstrated that the OTPA deep-learning model could convert noise signals into target point vibration signals, significantly reducing noise. At the SNR of -10 dB, the signal conversion accuracy, based on MAE values, indicated that the proposed approach exhibited approximately six times lower error and 50% higher fault diagnosis accuracy than conventional methods. In the case study using an operational electric vehicle, the signal conversion accuracy improved by 59% under various operational conditions compared to the conventional SVD method, and the fault diagnosis accuracy of the proposed approach improved by about 10% under new operational conditions compared to existing seat signal-based diagnostics.

The contributions of this research can be summarized in three key points. First, we proposed an approach that allows for the diagnosis of excited sources and transition locations in rotating machines without installed vibration sensors, using OTPA deep-learning model. Second, the proposed deep-learning model for OTPA demonstrated its capability to address nonlinearities occurring under various operational and fault conditions. Lastly, we introduced a deep learning model that effectively reduces the impact of external noise infiltrating during machine operation and amplifies the excited source's vibration signal.

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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, the M.S. degree in mechanical engineering from the Gwangju Institute of Science and Technology, Gwangju, Republic of Korea, in 2024, where he is currently pursuing the Ph.D. degree in mechanical engineering. His current research topics include prognostics and health management for rotating machines.

Hyunseok Oh received the B.S. degree in mechanical engineering from Korea University, Seoul, South Korea, in 2004, the M.S. degree in mechanical engineering from the Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2006, and the Ph.D. degree in mechanical engineering from the University of Maryland, College Park, MD, USA, in 2012. He is an Associate Professor with the School of the Mechanical Engineering, Gwangju Institute of Science and Technology, Gwangju, Republic of Korea. His research interests include fault diagnostics, industrial artificial intelligence, and inverse design.

Yong Hyun Ryu received the B.S. degree in mechanical design engineering from Chungang University, Seoul, Republic of Korea, in 2006. His current research topics include the development of harmonic performance for product vehicle and prognostics and health management for electric vehicles in Hyundai Motor Company.

Kyung-Woo Lee received the M.S. degree in 1994, and Ph.D. degree in 2000 in mechanical engineering from the Korea Advanced Institute of Science and Technology, Daejeon, South Korea. He has worked for R&D center in Hyundai Motor Company since 2001. His research interests include prognostics and health management for vehicles and future motilities.

Dae-Un Sung received the Ph.D. degree in mechanical engineering from Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2001. He is a research fellow and the lab. director of Vehicle Performance Degradation Research Lab. In Hyundai Motor Company. His research interests include PHM of power electric system and chassis of mobility vehicles.