Developing Generalized Health Index of Electric Vehicle Drivetrain

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ABSTRACT

Motors and reducers are core components of an electric vehicle's drivetrain. If either the motor or reducer fails, the vehicle cannot operate, and at high speeds, this poses a significant safety risk. Therefore, preventing failures in these components is critical for customer safety. However, most existing fault diagnosis models for electric vehicle drivetrains show limited performance under real driving conditions because load and speed vary continuously.

In this study, we propose a novel vibration signal generalization method that combines order tracking with physics-based amplitude adjustment techniques to improve diagnostic accuracy under variable operating conditions. Furthermore, we developed an AI model incorporating a health index that enhances generalization performance, enabling scalability across 5 different vehicle types

To achieve this, we designed a data processing technique that standardizes measurement data from various vehicle types by integrating domain knowledge, such as order analysis based on CAN bus speed information. The resulting health index successfully distinguishes deteriorated vehicles from normal ones regardless of vehicle type or driving conditions.

The findings of this study are expected to play a key role in applications under variable speed conditions.

1. INTRODUCTION

With the emergence of various future mobility platforms such as PBVs (Purpose-Built Vehicles), UAM (Urban Air Mobility), and robotaxis, electric vehicle (EV) systems utilizing motors and batteries, rather than conventional internal combustion engines, have been rapidly increasing. The motor and reduction gearbox are core components of the EV drivetrain, and any failure in these systems can render the vehicle inoperable. In particular, the failures occurring during high-speed driving pose a significant safety risk and therefore must be prevented.

To ensure customer safety, it is essential to develop technologies that can monitor faults in EV drivetrains and predict their remaining useful life (RUL). Recently, there has been a growing number of cases in which Prognostics and Health Management (PHM) technologies, using various sensors to measure the real-time condition of critical components and artificial intelligence algorithms to detect anomalies and predict remaining life, have been applied to mass-produced vehicles (Holland et al., 2010; Lee et al., 2019; Lee et al., 2023)

The authors have previously developed artificial intelligence (AI) model that diagnoses failures and predicts degradation levels of the drivetrain using vibration data measured under real driving conditions of EV (Lee et al., 2025; Oh et al., 2025). However, the developed health index cannot be directly operated across different vehicle types, since the OTPA (Operational Transfer Path Analysis) structure varies from one vehicle to another. Consequently, the threshold values of the health index cannot be reused. In other words, the magnitude and patterns of measured vehicle data vary by vehicle types, and the threshold values used to assess fault risk also change accordingly.

As a result, a new AI model must be developed for each vehicle platform by collecting vehicle-specific data and recalculating the degradation index and threshold values. This poses a significant limitation and may hinder the implementation of degradation monitoring functions for motors and reduction gearboxes at the mass-production stage.

In this study, we develop an artificial intelligence model that generates a generalized health index for EV drivetrains, enabling the use of vehicle-independent threshold values. The proposed approach is expected to play a critical role in establishing a platform for deploying our PHM technologies in future mass-produced vehicles.

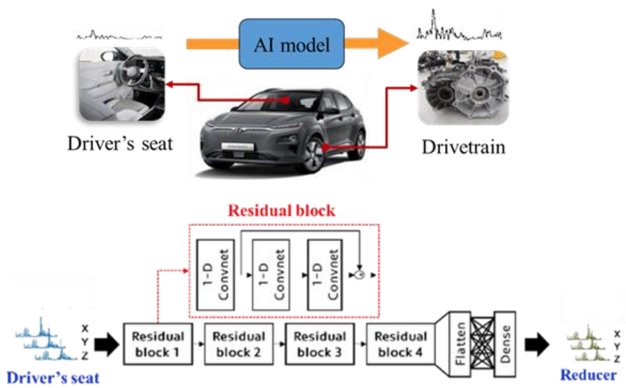


Figure. 1 AI model to detect anomalies and degradation level of EV drivetrain via OTPA concept (Lee et al., 2025)

2. Development of Signal Processing Methods for Measurement Data

Driving conditions cause variations in vehicle speed and motor rotational speed, which in turn lead to changes in the vibration signals of the drivetrain. In addition, because drivetrain specifications differ across vehicle types, the same level of physical degradation can result in different health index values depending on the vehicle. Consequently, it is not possible to define a unified threshold for the health index, and vehicle-specific threshold values become inevitable. This issue constitutes the most significant obstacle to the generalization of health indices.

To address this challenge, this study develops a signal processing method that normalizes measured signals independently of driving speed.

First, an order tracking technique is applied. Order tracking is a highly effective method for analyzing vibration signals from rotating machinery under variable-speed conditions. Rotating systems with faults generate periodic vibration components that differ from those observed under normal conditions. Order tracking enables the extraction of such periodic components by tracking vibration signals as a function of rotational order. By resampling the signal with respect to rotational angle rather than time, speed-dependent spectral components are transformed into stationary orders, allowing more effective fault detection.

However, in automotive drivetrains operating under a wide range of speed conditions, the amplitudes of measured vibration signals vary significantly due to centrifugal and tangential forces. Under such circumstances, conventional order tracking alone is insufficient for reliable fault detection. Centrifugal force increases proportionally to the square of rotational speed, whereas tangential force varies depending on torque and speed. During vehicle acceleration and deceleration, changes in acceleration and velocity create variations in driving resistance, which correspond to changes in tangential forces acting on the drivetrain (Lim et al., 2025). The total driving resistance and its components can be expressed as Eq. (1)~(4):

$$F_t = F_{rolling} + F_{drag} + F_{inertia} \tag{1}$$

$$F_{rolling} = \mu_{rr} \cdot m \cdot g \cdot \cos(\theta) \tag{2}$$

$$F_{drag} = \frac{1}{2}\rho \cdot C_d \cdot A \cdot v^2 \tag{3}$$

$$F_{inertia} = m \cdot a \tag{4}$$

where $F_{rolling}$, F_{drag} , and $F_{inertia}$ represent rolling resistance force, aerodynamic drag force, and inertia force, respectively. μ_{rr} is the rolling resistance coefficient, m is vehicle mass, g is gravitational acceleration, θ is road grade, ρ is air density, C_d is drag coefficient, A is frontal projection area, v is vehicle velocity, and a is acceleration.

In this study, these physical relationships are explicitly incorporated into the order tracking process to compensate for speed-dependent amplitude variations.

In addition, although motor rotational speed changes proportionally with vehicle load and speed, the data sampling rate remains constant. As a result, even when the underlying signal waveform is identical, higher vehicle speeds produce fewer samples per cycle, making waveform interpretation more difficult. As shown in the leftmost graph, the peak intervals differ. Because measurements are taken at fixed time intervals, the number of data points per cycle varies with speed: at lower speeds, more data points are recorded per cycle than at higher speeds.

To resolve this issue, the data were first upsampled to increase the number of samples, and then the cycle duration was equalized through phase alignment. Subsequently, the number of samples within a single cycle was standardized. Using this procedure, normalized vibration data can be obtained even under conditions where both amplitude and speed vary, as illustrated in figure 2.

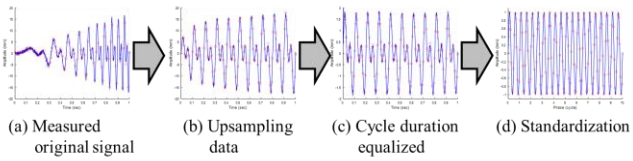


Figure. 2 Data standardization procedure

This study proposes a novel vibration signal generalization approach that combines order tracking with physics-based amplitude normalization, thereby overcoming the limitations of conventional methods. Using the proposed approach, consistent and reliable fault diagnosis performance was achieved across multiple vehicle types operating under variable-speed conditions.

3. MEASUREMENT OF FAULT DATA ACROSS DIFFERENT VEHICLE TYPES

3.1. Vehicle Data Acquisition

To develop a vehicle-independent health index, drivetrain vibration data were measured from a total of 14 electric vehicles across five different vehicle types. Vibration measurements were conducted at multiple locations, including the drivetrain, driver's seat, and mounting points, as illustrated in figure 3.

The test driving conditions consisted of rapid acceleration, mild acceleration, slow acceleration, and two constant-speed conditions at 80 km/h and 100 km/h.

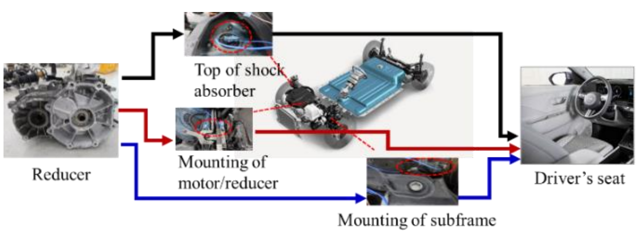
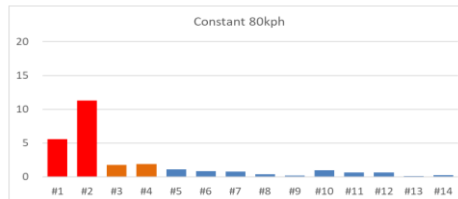


Figure 3. Data measurement points for developing the degradation model

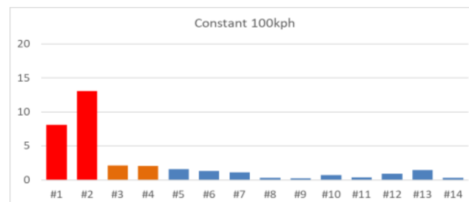
At automobile companies, many experts from various fields identify and improve issues in the vehicle development process through vehicle testing. These experts undergo years of training to detect even minute noises during driving that are difficult for the average person to hear. Through these experts' driving tests, the degradation levels of the EV drivetrain have been classified into three categories (severe, weak, normal). Vehicles #1 and #2 were classified as severe degradation level due to pronounced noise, whereas vehicles #3 and #4 exhibited weak but noticeable noise and were classified as weak degradation level. For the remaining vehicles, drivetrain noise was not perceptible to the driver and was therefore classified as the normal level.

3.2. Analysis of Vibration RMS Data

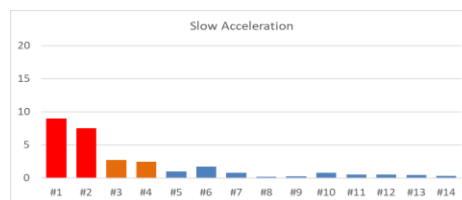
For each vehicle, the measured vibration data were processed to compute the root mean square (RMS) values, which were then averaged and plotted for each driving condition, as shown in figure 4. In the figure, red bars indicate the severe degradation group, orange bars indicate the weak degradation group, and blue bars represent the normal group. A clear separation between the severe and weak groups can be observed, while the weak group exhibits slightly higher RMS levels than the normal group.



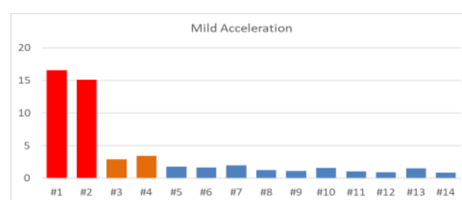
(a) Constant speed 80km/h



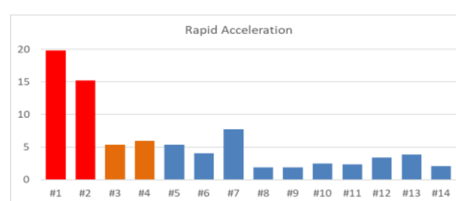
(b) Constant speed 100km/h



(c) Slow acceleration



(d) Mild acceleration



(e) Rapid acceleration

Figure 4. RMS results of the EV drivetrain

As the driving mode transitions from slow acceleration to mild acceleration and then to rapid acceleration, the accelerator pedal is increasingly depressed, resulting in faster increases in vehicle speed. As shown in figure 5, the RMS values increase as vehicle speed rises. In addition, RMS magnitude increases with the progression of drivetrain degradation. But the RMS of vehicle #7 (normal) at rapid acceleration is higher than that of vehicle #3 (weak) at all driving conditions.

Furthermore, vehicle #7 (normal) under the rapid acceleration condition exhibits higher RMS values than vehicles #1 (severe) under constant 80kph and shows similar RMS level with vehicles #1 (severe) under constant 100 kph and slow acceleration. This result indicates that it is difficult to use RMS values as a health index.

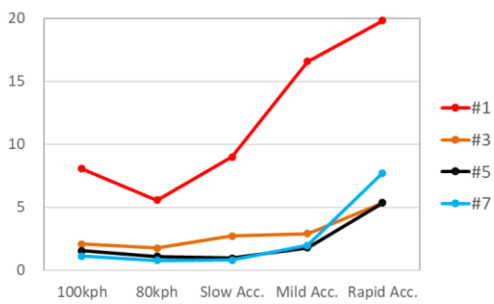


Figure 5. RMS values for vehicle #1 (severe), #3 (weak), #5 (normal) and #7 (normal)

4. DEVELOPMENT OF A GENERALIZED HEALTH INDEX

To estimate the health index, a multi-channel multilayer perceptron (MLP) model was employed, and a 1D convolutional neural network (1D-CNN) based architecture was designed to ensure robustness against speed variations. The output layer was configured with a single unit to produce a single degradation indicator, referred to as the health index. A ReLU activation function with upper and lower bounds of 1 and 0 was applied to the output layer, constraining the health index to a normalized range between 0 and 1 (Lee et al., 2025).

The AI model for the health index is developed using the data of vehicle type #1 with 7 vehicles having different degradation levels of drivetrain after the signal standardization explained in section 2. As usual, a portion of data from vehicle type #1 was used for training, and the rest was used for testing. Then the AI model is applied to the remaining 4 vehicle types with 7 different vehicles for the check of the generalized health index. The 3 degradation groups (severe, weak, normal) were successfully distinguished.

Figure 6 presents the health index results for 3 degradation groups (severe, weak, normal). Although there is some variation in health index with driving conditions, the dispersion is significantly reduced compared with the RMS-based results shown in figure 5. In particular, the health index under the rapid acceleration condition decrease to a level comparable to those obtained under other speed conditions, indicating a substantial improvement in consistency. Moreover the health index of vehicle #7 (normal) became lower than that of vehicle #3 (weak) and that of vehicle #1 (severe).

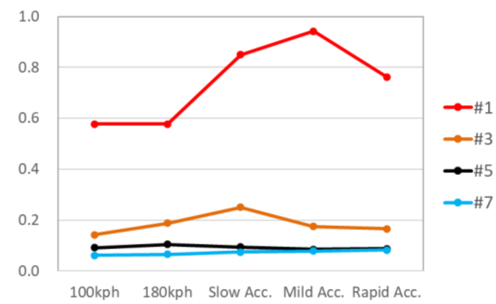
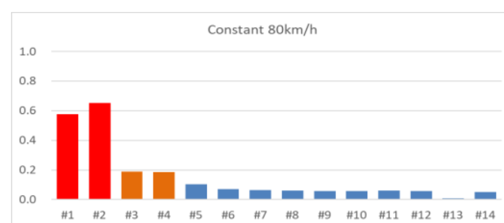
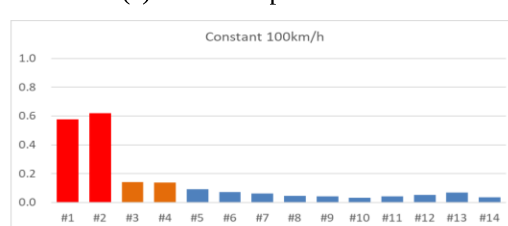


Figure 6. Health index for vehicle #1 (severe), #3 (weak), #5 (normal), and #7 (normal)

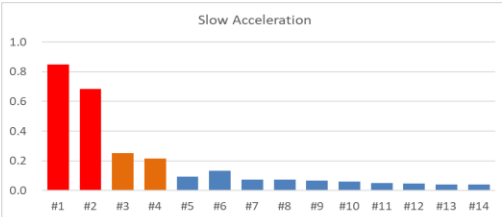
Figure 7 shows the health index results for all tested vehicles. Despite differences in vehicle types and drivetrain specifications, the severe, weak, and normal degradation groups are clearly distinguished. While the RMS values exhibited large discrepancies between the constant-speed conditions, the health index developed in this study significantly reduces such differences, providing a more stable and reliable indicator of drivetrain degradation. In particular, under the rapid acceleration condition, the health index of vehicle #7 (normal) shows lower values than those of vehicles #4 and #3 in the weak degradation. This result indicates that the misclassification observed when using RMS-based results is effectively corrected by the proposed health index



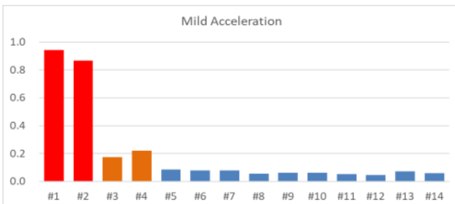
(a) Constant speed 80km/h



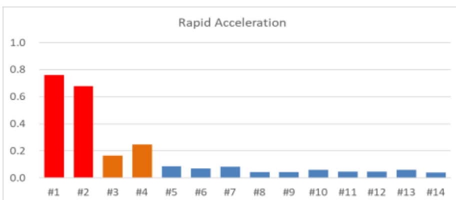
(b) Constant speed 100km/h



(c) Slow acceleration



(d) Mild acceleration



(e) Rapid acceleration

Figure 7. Health index of the EV drivetrain

5. CONCLUSION

In this study, a generalized health index with improved generalization performance was developed for the drivetrain of electric vehicles (EV), which are core systems of electric vehicle drivetrains, enabling its application across platform-derived vehicle types. The proposed health index provides consistent and reliable values regardless of vehicle type and driving condition, effectively overcoming the limitations of conventional vehicle-specific degradation metrics.

Future work will focus on studies related to onboard vehicle deployment. Efforts will be underway to further improve the robustness of the proposed algorithm against road-induced noise. To this end, vibration signals will be collected under a wide range of road surface conditions, including speed bumps, road humps, gravel roads, and manholes, and incorporated into the AI model training and validation process to enhance algorithm robustness.

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BIOGRAPHIES

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