Robust Fault Diagnosis of Electric Vehicle Drivetrain Using Amplitude Adjustment Techniques

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ABSTRACT

Most electric vehicle drivetrain fault diagnosis methods have been validated only under constant load and rotational speed conditions, showing limited performance in real driving environments where load and speed continuously vary. This study proposes a novel vibration signal generalization method that combines order tracking with physics-based amplitude adjustment techniques to improve diagnostic accuracy under variable operating conditions. Order tracking addresses the problem of the frequency variation of vibration signals that vary with speed over time. The proposed method converts vibration signals under variable speed conditions into pseudo-stationary signals of equivalent levels by adjusting amplitudes through factors that consider both centrifugal and tangential forces acting on rotating components in the drivetrain. To validate the effectiveness of the proposed technique, experiments were conducted using actual electric vehicles equipped with drivetrains at various degradation levels. Drivetrain vibration data were collected and evaluated across multiple operating scenarios. Experimental results demonstrate that the proposed method reduces variability across different speed conditions compared to raw signals. The proposed method shows promise for robust drivetrain diagnosis applications even under variable speed conditions, addressing a significant limitation of existing diagnostic approaches.

1. INTRODUCTION

Electric vehicle drivetrains consist of critical components, including electric motors, gearboxes, bearings, and power transmission elements, all of which are subject to various failure modes such as bearing degradation, gear tooth damage, rotor eccentricity, and winding faults (Lee et al., 2025). Early detection of these faults is crucial for preventing catastrophic failures, reducing maintenance costs, and ensuring vehicle safety. Vibration-based condition monitoring has emerged as one of the most effective approaches for drivetrain fault diagnosis due to its ability to detect incipient faults before they lead to complete system failure (Oh et al., 2025).

However, most existing vibration-based fault diagnosis methods for electric vehicle drivetrains have been developed and validated under controlled laboratory conditions with constant load and speed parameters. These methods typically assume stationary operating conditions where the rotational speed and load remain constant throughout the measurement period. While this assumption simplifies the analysis and enables the use of conventional frequency-domain techniques, it fails to capture the reality of actual driving conditions where speed and load continuously vary (Choi et al., 2025).

Order tracking has emerged as a promising technique for analyzing vibration signals from rotating machinery under variable speed conditions. By resampling the vibration signal with respect to the rotational angle rather than time, order tracking transforms speed-dependent spectral components into stationary orders, enabling more effective fault detection. However, the amplitude variations caused by changing centrifugal and tangential forces under different speed conditions remain a significant challenge that has not been adequately addressed in existing order tracking implementations.

The physical understanding of rotating machinery dynamics suggests that the vibration amplitudes are influenced by both the rotational speed and the forces acting on the rotating components. Centrifugal forces increase quadratically with rotational speed, while tangential forces vary with torque and speed conditions. These physics-based relationships provide valuable insights that can be leveraged to generalize vibration signals across different operating conditions, potentially improving the consistency and reliability of fault diagnosis under variable speed scenarios.

Previous research has partially leveraged these physical insights. For instance, Kim et al. (2024) attempted to generalize vibration signals across different speed conditions using a speed-squared term based on centrifugal force. However, this approach ignores the influence of torque variations during acceleration—namely, the tangential force—risking amplitude distortion and misjudgment of fault severity in real-world driving conditions. Therefore, an amplitude adjustment technique that considers both centrifugal and tangential forces is essential for fault diagnosis in electric vehicle (EV) driving scenarios involving various acceleration levels.

To overcome these limitations, this study proposes a novel vibration signal generalization method that combines order tracking with a physics-based amplitude adjustment. The proposed method aims to convert non-stationary vibration signals collected under variable speed conditions into pseudo-stationary signals with consistent amplitude levels, thereby enabling more reliable fault diagnosis in real-world EV applications.

The main contributions of this paper are as follows:

- We propose a new physics-based amplitude adjustment coefficient that integrates both centrifugal and tangential forces to effectively account for the complex variable speed and load conditions of EVs.
- We establish a comprehensive signal generalization pipeline that combines the proposed technique with order tracking to effectively remove both frequency and amplitude fluctuations.
- We experimentally validate our method on five real-world EVs under various acceleration scenarios, demonstrating a significant quantitative improvement in diagnostic robustness over conventional methods.

2. THEORETICAL BACKGROUND

2.1. Amplitude Adjustment

Vibration amplitude levels vary significantly across different speed conditions in rotating machinery. During rotational motion of drivetrain components, radial vibrations are primarily proportional to centrifugal forces, which can be expressed as Eq. (1):

$$F_c = mr\omega^2 \tag{1}$$

where m is the mass of the rotating component, r is the radius of rotation, and ω is the angular velocity. For a given system, only the rotational speed term ω^2 varies under different operating conditions.

Based on this physical relationship, Kim et al. (2024) proposed an amplitude adjustment method to generalize vibration signals across different speed conditions. The generalized amplitude can be expressed as Eq. (2):

$$A_{gen} = \frac{A_{raw}}{\omega^2} \tag{2}$$

where A_{raw} is the raw vibration amplitude and A_{gen} is the speed-generalized amplitude. This approach effectively equalizes vibration amplitudes from different speed domains under constant speed and constant load conditions.

3. PROPOSED METHOD

The amplitude adjustment method described in Section 2.1 is effective for different speed domains under constant speed and constant load conditions, but may not be effective under variable speed and variable load conditions. While conventional constant-speed and constant-load conditions only involve changes in the speed component of centrifugal forces, variable-speed and variable-load conditions also involve changes in torque. Rotational torque can be substituted with tangential forces, which, along with centrifugal forces, affect radial vibrations in drivetrain systems. Therefore, to generate generalized vibration amplitudes under variable speed and variable load conditions, it is necessary to consider both centrifugal and tangential forces.

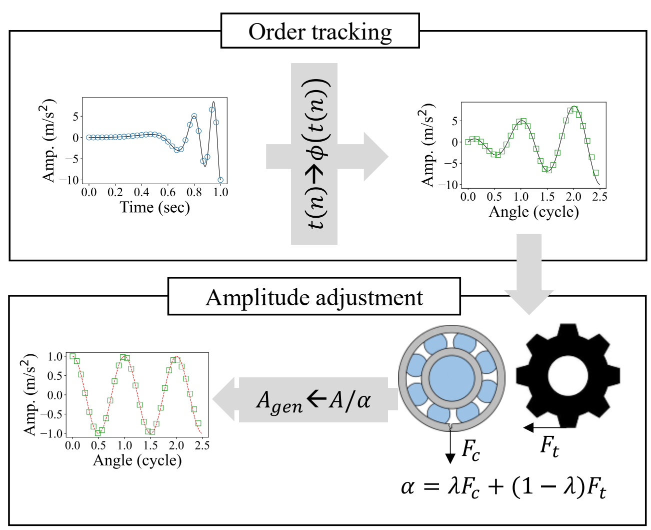
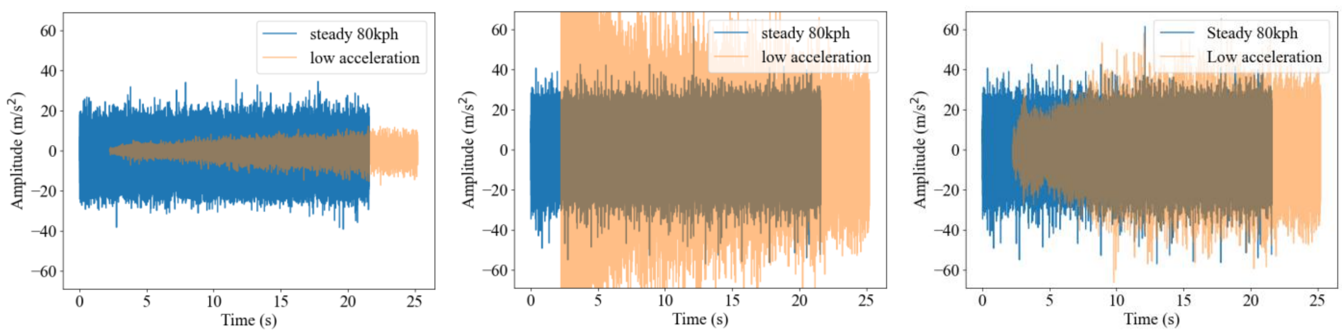


Figure 1. Proposed vibration generalization process



(a) (b) (c)

Figure 2. Comparison of vibration processing results of car #1 with new #1 drivetrain under steady 80 kph and low acceleration condition: (a) Raw signal; (b) Existing method; (c) Proposed method

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. (3), (4), (5), (6):

$$F_t = F_{rolling} + F_{drag} + F_{inertia} \tag{3}$$

$$F_{rolling} = \mu_{rr} mg\cos(\theta) \tag{4}$$

$$F_{drag} = \frac{1}{2}\rho C_d A v^2 \tag{5}$$

$$F_{inertia} = ma \tag{6}$$

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.

The proposed amplitude adjustment coefficient that considers both centrifugal and tangential forces is expressed as Eq. (7):

$$\alpha = \lambda F_c + (1 - \lambda) F_t \tag{7}$$

where λ is a weight coefficient that controls the relative influence of centrifugal and tangential forces. To create the most optimal generalized vibration amplitude, the weight coefficient is determined through optimization algorithms based on training data.

To maximize the stationary characteristics of vibration signals and equalize their scales, the objective function is formulated to minimize both the residual of RMS across different speed conditions and the gradient of RMS within each speed condition. This optimization approach ensures that the resulting generalized signals exhibit consistent amplitude characteristics across various operating conditions.

The complete signal processing procedure involves two main steps. First, order tracking is applied to raw vibration signals to generate frequency-invariant vibration signals with respect to speed variations. Subsequently, the amplitude adjustment coefficient, calculated using the optimized lambda and vehicle dynamics terms, is applied to create the final generalized vibration signal with invariant amplitude characteristics as depicted in Figure 1.

Table 1. Experimental setup

Vehicle		Real-scale test car		
Speed condition		Steady 80 kph, 100 kph, Low acceleration (0 ~ 50 kph) Mild acceleration (0 ~ 120 kph) Full acceleration (0 ~ 120 kph)		
Drivetrain condition		Nominal	Weak fault	Severe fault
Vehicle type	Car #1	New #1, Old #2	Old #3	Old #1, Old #4
	Car #2	New #1, Old #1		
	Car #3	New #1, Old #1		
	Car #4	New #1		
	Car #5	New #1	Old #1	
Measurement		Sampling rate: 25,600 Hz Location: Motor left hand x, y, z axes		

Table 2. Evaluation of amplitude adjustment methods

	Sum of RMS residuals (m/s^2)	Absolute sum of gradient of RMS (m/s^2)
Raw signal	74.80	1.45
Existing method	83.11	2.51
Proposed method	38.78	1.16

4. CASE STUDY

4.1. Experimental Setup

Vibration data were collected from various types of electric vehicles equipped with drivetrains having different mileage levels under both variable and constant speed conditions, as shown in Table 1. The experiments were conducted on five different vehicle scales under the following operating conditions: steady 80 kph, steady 100 kph, low acceleration, mid acceleration, and full acceleration. The drivetrain health classes were categorized into three levels: normal, weak fault, and severe fault.

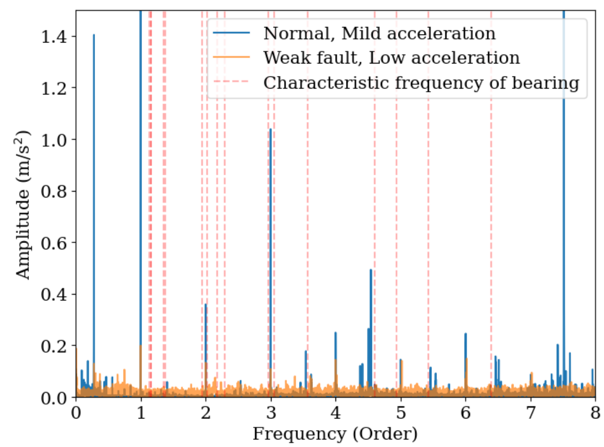
Accelerometer sensors with a sampling rate of 25,600 Hz were attached to the x, y, and z axes of the drivetrain, and three measurements were taken for each condition. Additionally, encoder sensors were used to acquire rotational speed data of the drivetrain, and acceleration data were obtained through numerical differentiation of the speed signals.

For optimization of the weight coefficient, datasets 1 and 2 from Car #1 with New #1 drivetrain were used as training data, while the remaining datasets served as test data. The Brent optimization method was employed to calculate the optimized weight coefficient λ for each axis (x, y, z) independently.

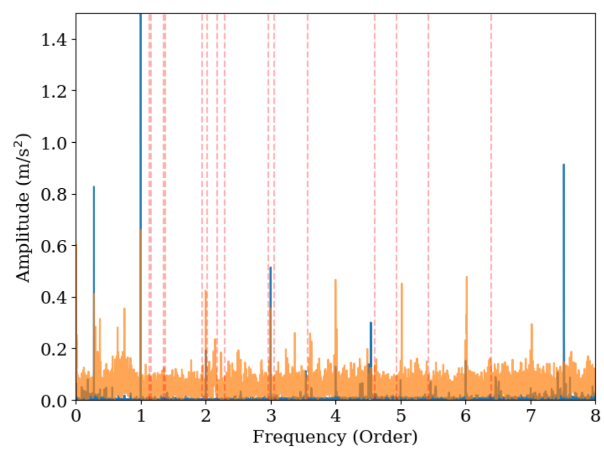
4.2. Results

The results of applying the proposed method to generalize vibration data under variable speed conditions are presented in Figure 2. This figure compares the z-axis vibration data from Car #1 with New #1 drivetrain under steady 80 kph and low acceleration conditions. Figure 2(a) shows the raw signal, which clearly demonstrates scale differences between the two conditions, with the low acceleration data showing progressively increasing amplitude as speed increases. Figure 2(b) presents the results after applying the conventional amplitude adjustment based on the speed-squared term. This method showed no significant reduction in scale differences and, critically, exhibited an amplitude divergence phenomenon in the low-speed region of the low acceleration condition. This divergence occurs because the conventional method divides the amplitude by the speed-squared term (ω^2), which approaches zero at low speeds, causing the value to become unstable. In contrast, Figure 2(c) displays the results using the proposed vehicle dynamics-based amplitude adjustment. The proposed method demonstrated superior scale difference reduction and amplitude consistency. By incorporating the tangential force (F_t) term based on vehicle dynamics, it ensures stable and effective normalization even at low speeds, avoiding the divergence issues of the conventional approach.

To quantitatively evaluate the generalization performance of the proposed method, the average sum of RMS residuals and the average absolute sum of gradient of RMS were calculated for all speed condition data across each vehicle type and health class. The results presented in Table 2 demonstrate that the proposed method achieved lower RMS residuals and gradients compared to conventional method, confirming its superior ability to create consistent, pseudo-stationary signals.



(a)



(b)

Figure 3. Comparison of order spectrum for normal and faulty drivetrains: (a) before applying the proposed amplitude adjustment; (b) after applying the proposed amplitude adjustment

Table 3. Comparison of fault diagnosis accuracy by signal processing method

	Accuracy (%)
Raw signal	75.68
Existing method	76.31
Proposed method	86.79

Under variable speed conditions, the significant influence of speed can mask the characteristic features of a drivetrain fault, posing a major challenge for accurate diagnosis. To investigate this, Figure 3 compares the order spectrum of a healthy drivetrain (Car #1, New #1) under mild acceleration with that of a drivetrain with a weak fault (Car #1, Old #3) under low acceleration. Figure 3(a) shows the results without amplitude adjustment. Although the weakly faulty drivetrain (Old #3) exhibits broad excitation across the order spectrum, its amplitude at high-order rotational and characteristic bearing frequencies is notably lower than that of the healthy drivetrain. This masking effect could easily lead to a misdiagnosis, where a faulty component is classified as healthy. Figure 3(b), however, shows the results after applying the proposed amplitude adjustment. The fault signatures are now clearly enhanced. The overall excitation across the spectrum from the drivetrain degradation is more prominent, and the amplitudes at high-order rotational frequencies and bearing characteristic frequencies are correctly shown to be greater than those of the healthy condition.

This enhancement directly translates to improved diagnostic accuracy. Table 3 presents the results of a fault diagnosis classification based on the RMS energy level of the vibration signals. Using thresholds of 1.2 m/s^2 (to distinguish normal from weak fault) and 4.0 m/s^2 (to distinguish weak from severe fault), the diagnostic accuracy for both the raw signal and the signal adjusted by the conventional method was approximately 75%. In contrast, the proposed method achieved a diagnostic accuracy of approximately 87%, demonstrating a significant improvement.

These results validate the effectiveness of incorporating both centrifugal and tangential force considerations in the amplitude adjustment process. The physics-based approach successfully addresses the limitations of existing methods when applied to variable speed and load conditions, providing a more robust foundation for fault diagnosis in real-world electric vehicle applications.

5. CONCLUSION

This study proposed a novel vibration signal generalization method that combines order tracking with physics-based amplitude adjustment to improve fault diagnosis accuracy under variable operating conditions in electric vehicle drivetrains. The key contributions and findings of this research can be summarized as follows.

The proposed signal processing approach effectively transforms non-stationary vibration signals into pseudo-stationary signals. This transformation enables the application of conventional fault diagnosis techniques to signals collected under variable operating conditions, significantly expanding the practical utility of existing diagnostic methods.

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REFERENCES

Choi, M., Lee, C., Park, S., Hwang, M., & Oh, H. (2025). Frequency-enhanced network with self-supervised learning for anomaly detection of hydraulic piston pumps. *Expert Systems with Applications*, *282*, 127662.

Kim, I., Kim, S. W., Kim, J., Huh, H., Jeong, I., Choi, T., Kim, J., & Lee, S. (2024). Single domain generalizable and physically interpretable bearing fault diagnosis for unseen working conditions. *Expert Systems with Applications*, *241*, 122455.

Lee, D., Lee, J. G., Choi, M., Park, C., Kim, C. W., Niu, G., & Oh, H. (2025). Multi-fidelity sub-label-guided transfer network with physically interpretable synthetic datasets for rotor fault diagnosis. *Engineering Applications of Artificial Intelligence*, *148*, 110467.

Lim, H., Lee, J. W., Boyack, J., & Choi, J. B. (2025). EV-PINN: A Physics-informed neural network for predicting electric vehicle dynamics. in Proceedings of the IEEE International Conference on Robotics and Automation.

Oh, J., Yoo, D., Kim, C., Oh, H., Ryu, Y., Lee, K.-W., & Sung, D.-U. (2025). A hybrid fault diagnostic approach using operational transfer path analysis and denoising deep learning with remote sensors: Application to electric vehicles. *Expert Systems with Applications*, *270*, 126470.

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