

Article

Effects of Road Surface Excitation on Eccentricity in In-Wheel PMSMs and a Torque-Ripple Current Index for Fault Detection

Quoc Trieu Nguyen ^{1,2} , Van Nghia Le ² , Anh Duc Nguyen ² , Van Hieu Nguyen ²  and Valentin Ivanov ^{1,*} 

¹ Smart Vehicle System Working Group, Technische Universität Ilmenau, 98693 Ilmenau, Germany; trieun.nguyen-quoc@tu-ilmenau.de

² Department of Vehicle and Energy Conversion Engineering, School of Mechanical Engineering, Hanoi University of Science and Technology, Hanoi 100000, Vietnam; nghia.levan@hust.edu.vn (V.N.L.)

* Correspondence: valentin.ivanov@tu-ilmenau.de

Abstract

This study investigates the influence of road-induced vertical excitation on air-gap eccentricity in in-wheel permanent magnet synchronous motors. A coupled electromechanical simulation framework is developed by integrating a field-oriented controlled PMSM model, a quarter-vehicle vertical dynamics model, and stochastic road roughness generated according to the ISO 8608. The proposed motor model is validated against experimental data obtained from a dynamometer test bench. Mixed eccentricity conditions are introduced to investigate how road excitation affects air-gap variation and motor current characteristics. A normalized torque-ripple current index is then extracted from the time-domain features of the q-axis current i_q , which can be readily calculated from the phase currents and rotor position available in conventional inverter drives without requiring additional sensors. The simulation results reveal that road excitation significantly increases the fluctuation of air-gap eccentricity and amplifies torque-ripple-related current variations compared with no-road conditions. Furthermore, the proposed index increases consistently with eccentricity severity, while rougher road profiles shift the current response toward higher abnormality levels. These findings demonstrate that road–motor coupling has a significant impact on electrical fault signatures and should be considered when developing current-based condition monitoring methods for in-wheel PMSMs. The proposed framework provides a validated basis for evaluating eccentricity faults and supports the development of robust fault diagnosis techniques under realistic vehicle operating conditions.

Keywords: in-wheel motor; PMSM; eccentricity; unbalanced magnetic force; road excitation; abnormal detection



Academic Editors: Lihui Zhao and Christoph Bleicher

Received: 1 July 2026

Revised: 21 July 2026

Accepted: 30 July 2026

Published: 1 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The electrification of the transport sector has received widespread attention due to the growing need to avoid fossil fuel depletion and environmental pollution. With the widespread use of electric vehicles, in-wheel motors (IWMs) have recently received considerable attention because of their compact design, superior efficiency, rapid torque response, and ability to control individual wheels [1,2]. This design eliminates the need for the rest of the mechanical drivetrain system, including the clutch, gearboxes, and mechanical differentials in conventional vehicles, thereby offering several prominent advantages, including improved system efficiency, reduced mechanical maintenance, improved control at the wheel level, and in-vehicle space conservation [2,3]. Nonetheless, the use of IWMs in passenger cars is presently hampered by certain critical engineering issues [2,4].

The first of these issues is the rise in unsprung mass. For instance, whereas central-drive systems integrate the motor within the sprung mass, in-wheel systems cause an average rise of 20–50 kg in unsprung mass in wheels [5,6]. This major mass effect entirely changes the dynamics, along with a drop in the natural frequency of the wheel-hop mode from 14 Hz to nearly 10 Hz, thus potentially worsening ride comfort and road-holding stability [5,7,8]. More importantly, higher unsprung mass amplifies dynamic wheel loads and suspension travel—particularly on rough road surfaces—thereby reducing ride quality and compromising vehicle handling performance [9,10].

A key challenge in IWM systems arises from the coupled interaction between road-induced excitation and the motor's air-gap eccentricity [11,12]. Because the in-wheel motor rotates concentrically with the wheel, it is directly exposed to vibrations and impacts generated by the road. Vertical forces induced by uneven road surfaces impose dynamic loads on the motor bearings, which can initiate or aggravate rotor eccentricity faults [11,13]. Eccentricity—defined as the deviation of the rotor's geometric center from the stator's magnetic center—typically appears in three forms: static eccentricity (a fixed offset between rotor and stator centers), dynamic eccentricity (the rotor center revolving around the stator center), and mixed eccentricity (a combination of both) [14–17]. The consequences of eccentricity are multifaceted and mutually reinforcing. First, a non-uniform air-gap distribution produces an unbalanced magnetic force (UMF), generating radial loads that can reach several hundred newtons and thereby accelerating bearing wear, with the potential to trigger major motor failures [18]. Second, air-gap modulation induces torque ripple and electromagnetic vibration, which can propagate through the suspension system and degrade ride comfort [11,13,19]. Third, and particularly relevant for IWM applications, road-induced vertical acceleration alters the effective air-gap kinematics during operation, rendering the eccentricity time-varying and amplifying its effects relative to smooth-road conditions [11]. Because bearing degradation itself often initiates rotor displacement and eccentricity, while eccentricity in turn increases radial loading and accelerates bearing wear [18,20], these mechanisms collectively establish a self-reinforcing degradation loop: increased road roughness promotes eccentricity, eccentricity elevates vibration and bearing loading, and the resulting wear further amplifies eccentricity-induced effects.

Currently, in-wheel traction systems predominantly adopt permanent magnet synchronous motors (PMSMs) due to their superior performance characteristics compared with alternative machine types; consequently, a substantial body of research has focused on fault analysis in PMSMs, commonly categorizing faults into electrical, mechanical, and magnetic classes [2]. It is widely reported that approximately 40–50% of electrical motor failures are attributable to mechanical faults [20–23], which are largely associated with bearing defects and rotor eccentricity. In parallel, existing eccentricity-detection studies for PMSMs can be broadly grouped into three methodological families: signal-based, model-based, and data-driven approaches [17].

Signal-based techniques, most notably Motor Current Signature Analysis (MCSA), remain prevalent in the literature because they are non-intrusive and readily compatible with the current sensors already available in drive inverters [24,25]. In principle, MCSA identifies eccentricity by tracking characteristic frequency components in the stator current spectrum. However, important limitations arise in IWM applications. First, MCSA performance deteriorates under non-stationary operating conditions, where speed varies continuously during normal driving. Second, eccentricity-induced current harmonics may be masked by load-torque fluctuations and closed-loop control dynamics, particularly in vector-controlled drive systems. Third, reliable spectral separation typically requires FFT-based analysis with sufficient frequency resolution, which in turn demands long data acquisition windows and constrains real-time monitoring. Model-based approaches rely

on parameter estimation or observer techniques, for example, by tracking changes in the d-axis inductance, which decrease with increasing eccentricity severity due to magnetic saturation changes [26]. While such methods can be effective in standstill conditions, they depend on accurate machine models and are sensitive to parameter uncertainties arising from temperature variation, saturation, and operating-point changes.

Data-driven methods based on machine learning (ML) and deep learning (DL) have shown classification accuracies exceeding 90% for multi-fault diagnosis in PMSMs [27,28]. Techniques including convolutional neural networks (CNNs), support vector machines (SVMs), and hybrid architectures have been applied to classify eccentricity-related faults using current and vibration signals. However, these approaches require extensive labeled training datasets encompassing various fault severities and operating conditions—data that are often unavailable in practical IWM applications [17,29]. Moreover, many DL models function as “black boxes” with limited physical interpretability, making it difficult for engineers to validate fault detection decisions or understand failure mechanisms [29].

Despite extensive research on PMSM fault detection, several important gaps remain for IWM applications. Many studies have examined static, dynamic, and mixed eccentricity through stator-current spectra, but as noted above, such frequency-domain approaches remain computationally demanding and are less suited to real-time deployment under dynamically varying loads. Time-domain statistical descriptors, such as kurtosis and skewness, have shown promise for identifying eccentricity in induction machines using relatively simple vibration or current measurements, offering a lower-complexity alternative that does not rely on frequency transforms; yet these descriptors remain underexplored for PMSMs, particularly for in-wheel motors, where road-induced vibration can exacerbate dynamic eccentricity. When such descriptors are combined with ML classifiers, however, they inherit the same data-labeling and computational burden discussed above, limiting their alignment with embedded diagnosis. In addition, while the coupled influence of road profiles on motor eccentricity has been investigated for in-wheel switched-reluctance machines—highlighting how road excitation amplifies air-gap variation and unbalanced forces—these effects are rarely incorporated into eccentricity detection schemes tailored to in-wheel configurations.

Recent studies have also begun extending PMSM condition monitoring beyond classical signal, model, and data-driven methods. Physics-informed neural networks (PINNs) are increasingly combined with deep learning for eccentricity and fault classification [30]. Digital-twin frameworks integrating PINNs, Kalman-filter sensor fusion, and residual-based classifiers have been proposed for real-time PMSM diagnosis in EV traction applications [31,32]. Edge-AI implementations enable lightweight, low-latency fault detection directly on embedded/inverter hardware [33,34], while multi-sensor fusion of current, vibration, and other signals has been shown to improve fault discriminability [35]. However, these advances remain largely decoupled from road-induced excitation effects, motivating the coupled road–eccentricity–current framework proposed here.

This study quantifies how road-induced vertical excitation amplifies air-gap eccentricity and UMF in PMSM in-wheel motors, and evaluates whether the resulting electromechanical modulation can be observed through iq-based time-domain indicators. A high-fidelity model was developed in MATLAB/Simulink. To assess the model’s credibility under healthy operating conditions, measured datasets obtained from the physical motor operating normally were used for benchmarking. The model was then employed to examine the UMF and motor current signals under different road conditions and eccentricity levels. This study is limited to simulation-based analysis. The proposed index is intended to demonstrate the observability of eccentricity-induced modulation rather than to claim field-ready diagnostic performance.

The remainder of the paper is organized as follows. Section 2 introduces the theoretical background, including the electromechanical PMSM model, the influence of eccentricity on air-gap distribution, unbalanced magnetic force, and the coupling mechanisms between road excitation and motor dynamics. Section 3 presents and discusses the results concerning how road-induced excitation, in combination with varying eccentricity levels, influences the UMF and the fluctuations in motor current. Finally, Section 4 concludes the paper and outlines directions for future work toward predictive maintenance in IWM electric vehicles based on richer, multi-sensor fusion frameworks.

2. Theoretical Background

2.1. Eccentricity

Eccentricity in PMSMs refers to a non-uniform air gap between the rotor and stator, which leads to an uneven magnetic flux distribution and can adversely affect both motor performance and reliability [22]. As reported by Zhiyuan Li et al., eccentricity is among the most common mechanical fault types in rotating electrical machines and accounts for a substantial share of the faults documented in the literature and in field reports [28]. As illustrated in Figure 1, eccentricity in rotating machines is classified into three categories according to the geometric relationship between the stator bore center and the rotor geometric center [36,37]:

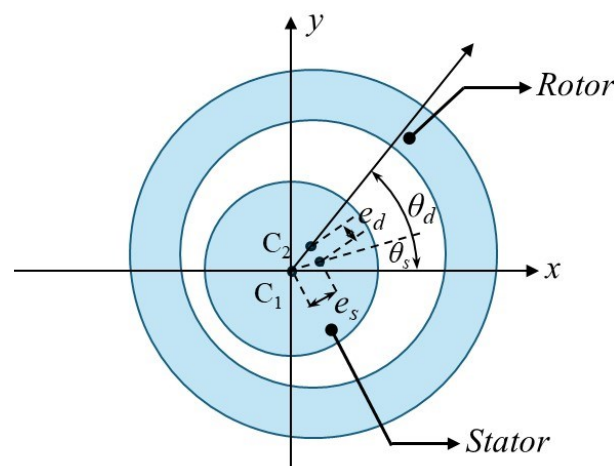


Figure 1. Eccentricity in IWM.

- Static Eccentricity (SE): The rotor center C_2 coincides with the rotation axis, but this axis is displaced from the stator bore center C_1 by a distance of e_s . The position of the minimum air gap remains stationary in the stator reference frame [38,39].
- Dynamic Eccentricity (DE): The rotor center C_2 is offset from the rotation axis by a distance of e_d , causing the rotor to orbit around the stator center. The position of the minimum air gap rotates with the rotor at mechanical frequency θ [36,38,40].
- Mixed Eccentricity (ME): A combination of both static and dynamic eccentricity, where $e_s \neq 0$ and $e_d \neq 0$ [37,41].

In the healthy PMSM IWM, the air-gap length is constant (g_0). However, in the eccentricity condition, the rotor–stator air gap will vary depending on the space angle and road excitation [40]. Thus, a PMSM IWM air gap in the vertical direction under ME fault can be expressed as follows [42]:

$$g(\theta, t) = g_0 - e_s \cos(\theta_s - \theta) - e_d \cos(\omega_r t - \theta + \theta_d) - e_r \quad (1)$$

where θ is the rotor angle, θ_s is the static eccentricity angle, θ_d is the dynamic eccentricity angle, and e_r is the eccentricity resulting from the influence of road surface vibrations on the IWM.

The mixed eccentricity severity is defined as the ratio of the total eccentricity to the nominal air-gap, expressed as:

$$\epsilon = \frac{e_s + e_d}{g_0} \times 100\% \quad (2)$$

2.2. PMSM Motor Model

For PMSMs employed in vector control applications, the three-phase abc stationary reference frame is transformed into a two-phase d-q rotating reference frame aligned with the rotor using Park's transformation [43–46]. This transformation eliminates the time-varying inductances inherent in the abc frame and simplifies the motor equations, making them more amenable to control design and fault analysis [47]. The Park transformation is defined as:

$$\begin{bmatrix} f_d \\ f_q \\ f_0 \end{bmatrix} = \begin{bmatrix} \cos(\theta_e) & \cos(\theta_e - \frac{2\pi}{3}) & \cos(\theta_e + \frac{2\pi}{3}) \\ -\sin(\theta_e) & -\sin(\theta_e - \frac{2\pi}{3}) & -\sin(\theta_e + \frac{2\pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} f_a \\ f_b \\ f_c \end{bmatrix} \quad (3)$$

where f represents voltage, current, or flux linkage quantities, and $\theta_e = N_p \theta_m$ is the electrical angle (N_p is the number of pole pairs, and θ_m is the mechanical rotor position).

Applying Park's transformation to the three-phase stator voltage equations yields the d-q axis voltage equations [43–45]:

$$u_d = R_s i_d + L_d \frac{di_d}{dt} - \omega_e L_q i_q \quad (4)$$

$$u_q = R_s i_q + L_q \frac{di_q}{dt} + \omega_e L_d i_d + \omega_e \psi_f \quad (5)$$

where

u_d, u_q : d-axis and q-axis voltages (V);

i_d, i_q : d-axis and q-axis currents (A);

R_s : stator resistance per phase (Ω);

L_d, L_q : d-axis and q-axis inductances (H);

$\omega_e = N_p \omega_m$: electrical angular velocity (rad/s);

ψ_f : permanent magnet flux linkage (Wb).

The electromagnetic torque of the PMSM can be expressed as:

$$T_e = \frac{3}{2} N_p i_q [(L_d - L_q) i_d + \psi_f] \quad (6)$$

The equation of motion of the PMSM can be expressed as follows:

$$T_e - T_L = J \frac{d\omega_m}{dt} + B\omega_m \quad (7)$$

where T_L is the motor load torque; J is the moment of inertia of the motor; ω_m is the mechanical angular speed of the rotor; and B is the friction coefficient.

2.3. Unbalanced Magnetic Force (UMF)

As the position of the rotor center changes, the value of the stator–rotor air gap will vary with the position. The uneven air gap causes an irregular distribution of magnetic permeability, resulting in an irregular air-gap magnetic field. The irregular air-gap magnetic field accelerates the rotor, producing an uneven radial force, which is the UMF [12,48].

The process for determining the vertical UMF is formulated based on the analytical air-gap field model and Maxwell stress approach proposed in [42,49], which has been widely adopted for eccentricity analysis in PMSMs. First, because eccentricity causes the air-gap length to vary with the circumferential angle, the air-gap permeance is defined as:

$$\Lambda(\theta, t) = \frac{\mu_0}{g(\theta, t)} \quad (8)$$

where μ_0 is the permeability of free space. Under the linear air-gap assumption, the radial air-gap flux density is obtained from the product of the resultant magnetomotive force (MMF) and the air-gap permeance:

$$B_r(\theta, t) \approx F(\theta, t)\Lambda(\theta, t) \quad (9)$$

where $F(\theta, t)$ denotes the total MMF in the air gap and is determined by the magnetomotive force generated by the rotor permanent magnets and the magnetomotive force produced by the three-phase stator winding currents. Next, the radial magnetic pressure acting on the air-gap surface is computed using Maxwell stress. Since the tangential air-gap flux density B_t is much smaller than the radial component B_r , the radial magnetic pressure is primarily determined by B_r and can be approximated as follows [49]:

$$f_r(\theta, t) = \frac{B_r^2(\theta, t)}{2\mu_0} \quad (10)$$

Finally, the vertical UMF is obtained by projecting the radial pressure onto the vertical axis and integrating it over the air-gap circumference. Since the present study focuses on the influence of road-induced vertical vibration, only the vertical component of the radial magnetic force is considered. The vertical projection directly interacts with the quarter-car dynamics described in Section 2.4, whereas the circumferential force component mainly contributes to torque production and is therefore beyond the scope of this work. The vertical force is given by:

$$F_{UMF,z} = LR \int_0^{2\pi} f_r(\theta, t) \sin \theta d\theta \quad (11)$$

where R is the rotor radius, and L is the air-gap axial length.

2.4. Vertical Dynamics Model

Vertical vehicle vibrations provide a valuable source of information for characterizing system dynamics and revealing electromechanical anomalies in the drivetrain. The air-gap eccentricity is not constant; under real operating conditions, it varies with road-induced excitation. In vehicles equipped with in-wheel motors, rotor eccentricity generates endogenous excitation forces that act directly on the motor–wheel assembly, thereby producing a pronounced impact on motor operating conditions [50].

In this study, the vertical dynamics are represented as a linear multi-degree-of-freedom system comprising the wheel, the in-wheel motor, and the vehicle body to examine how road excitation influences motor eccentricity and the resulting vertically oriented unbalanced magnetic force. To capture the road–motor coupling while keeping the model

tractable for repeated electromechanical simulation, a quarter-vehicle representation with four degrees of freedom is adopted, as illustrated in Figure 2. This configuration is chosen because, unlike a conventional quarter-car model in which the wheel assembly is treated as a single lumped mass, the in-wheel motor introduces an additional internal degree of freedom between the stator and the rotor, connected through the bearing stiffness. This extra degree of freedom is essential, since it is precisely the relative motion between the stator and the rotor that determines the instantaneous road-induced air-gap variation, thereby forming the physical link between road excitation and electromagnetic eccentricity. The suspension connects the body to the stator, while the tire connects the rotor–wheel assembly to the road profile. All spring and damping elements are assumed to be linear, and roll, pitch, and longitudinal dynamics are neglected, consistent with the common simplification used in quarter-car ride-comfort studies.

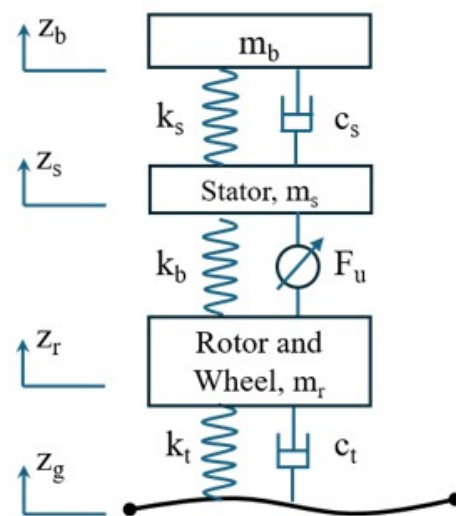


Figure 2. Dynamic model of road–motor coupling system.

For the electric vehicle equipped with an in-wheel PMSM, the stator is mounted to the vehicle chassis and the outer bearing race, whereas the rotor is coupled to the inner bearing race. The wheel assembly mass is decomposed into two parts: the combined mass of the tire, rim, and rotor, denoted by m_r , and the mass of the stator together with associated structural components, denoted by m_s . These two masses are connected through the bearing, whose equivalent stiffness is represented by k_b . Rotor eccentricity alters the air gap between the rotor and stator, producing an unbalanced radial magnetic force. Its vertical component, denoted by $F_{UMF,z}$, is derived in Section 2.3. In developing the vehicle model, different classes of road excitation are considered to capture their effects on rotor motion, overall vehicle dynamic response, and the vertical motion of the stator. Based on Newton’s second law, the equations of motion of the active suspension system can be written as follows:

$$m_b \ddot{z}_b + k_b(z_b - z_s) + c_s(\dot{z}_b - \dot{z}_s) = 0 \quad (12)$$

$$m_s \ddot{z}_s + k_s(z_s - z_b) + c_s(\dot{z}_s - \dot{z}_b) + k_b(z_s - z_r) - F_u = 0 \quad (13)$$

$$m_r \ddot{z}_r + k_t(z_r - z_g) + c_t(\dot{z}_r - \dot{z}_g) + k_b(z_r - z_s) + F_u = 0 \quad (14)$$

where z_b , z_s and z_r are the vertical displacements of the body mass m_b , stator and rotor; z_g represents the road excitation; and k_s and c_s denote the suspension stiffness and suspension damping.

In the model, road-induced eccentricity is modeled as the result of relative mechanical motion between the rotor/wheel assembly and the stator-side structure rather than a

direct electromagnetic disturbance. Road excitation causes vertical motion of both parts, and their mismatch produces a relative rotor–stator displacement, which is treated as an additional eccentricity component. This eccentricity alters the air-gap distribution, leading to non-uniform magnetic permeance and flux density, which in turn generates unbalanced magnetic force. The resulting electromagnetic disturbance contributes to torque ripple and is reflected in the q-axis current under FOC, forming a coupling path from road excitation to mechanical displacement, air-gap variation, electromagnetic asymmetry, and current response.

2.5. Road Excitation Generation

Road surface roughness is coupled with electromechanical irregularities in IWMs—most notably air-gap eccentricity—through vibration excitation of the wheel–motor assembly and the resulting variations in drivetrain loading [50,51]. Under different road conditions, changes in vertical excitation lead to different vibration levels of the stator and rotor, which in turn modulate the UMF and torque ripple, thereby amplifying motor vibration [52,53]. Consequently, a reliable assessment of normal versus abnormal operating states based on readily available operating signals requires a systematic analysis of road-profile effects and the coupled interaction between road excitation and eccentricity on measurable quantities.

In this study, the focus is to clarify to what extent road conditions affect eccentricity in the in-wheel motor’s current and speed signals. This section, therefore, examines, in a quantitative manner, how road roughness and vehicle speed influence the variability of current and rotational speed, and evaluates the implications for discriminating motor states across different eccentricity levels.

ISO 8608:2016 [54] provides a standardized framework for characterizing road surface roughness using the power spectral density (PSD) of the vertical displacement of the road profile [55,56]. The PSD describes how the variance in road elevation is distributed over spatial wavelengths. Under ISO 8608, the displacement PSD $G_d(n)$ as a function of spatial frequency n (cycles/m) is commonly approximated by [57]:

$$G_d(n) = G_d(n_0) \left(\frac{n}{n_0} \right)^{-\omega} \quad (15)$$

where $G_d(n)$ is the displacement PSD at spatial frequency n ; $G_d(n_0)$ is the reference displacement PSD (its relationship with road roughness levels is shown in Appendix A Table A1); n is the spatial frequency (cycle/m); and ω is the frequency exponent, usually $\omega = 2$ in road spectrum classification [58].

Four time-domain approaches are commonly used to generate single-point models with random excitation of pavement unevenness: the white-noise filtering method, harmonic superposition, discrete sampling based on the PSD, and discrete time-series generation methods [59,60]. Among these, the white-noise method is often preferred because it is numerically stable, is computationally efficient, and enables fast simulation with relatively low implementation complexity [60]. In this paper, the white-noise approach is adopted to construct the road roughness function. Accordingly, the time-domain model of the road input applied at a single wheel (single-wheel pavement excitation) can be expressed as follows [61]:

$$\dot{z}_g(t) = -2\pi f_0 z_g(t) + 2\pi \sqrt{G_d(n_0)} v w(t) \quad (16)$$

where v is vehicle speed, and f_0 is the cut-off frequency of the pavement.

To investigate the coupling mechanism between road-induced vertical excitation and UMF in IWM systems, road profile inputs were synthesized with a primary focus on class

B and class C road surfaces at a driving velocity of 80 km/h, since this condition reflects the real driving environment. Figure 3 shows the generated random road profiles classified by ISO at a constant vehicle speed of 80 km/h.

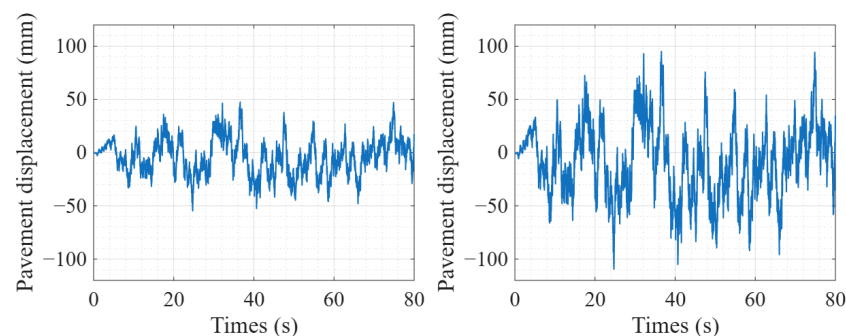


Figure 3. Road class B (left) and road class C (right) profiles at 80 km/h.

Classes B and C were chosen to represent the smooth-to-moderately rough spectrum when road–motor coupling first becomes pertinent, while still reflecting standard passenger car operating. Class A generates vertical excitation insufficient to significantly affect the air gap in comparison to the inherent electromagnetic ripple, while classes D and higher exhibit substantially deteriorated surfaces that may amplify the coupling beyond standard usage. Deterministic transient events, including potholes and speed bumps, are excluded due to their violation of the stationarity assumption inherent in the ISO 8608 PSD description and the sliding-window RMS statistics; these events generate isolated transient spikes that are more appropriately handled by event-detection methods and will be considered in future work.

3. Results and Discussion

The proposed diagnostic approach and the coupling between road excitation and eccentricity faults were implemented in MATLAB/Simulink. As can be seen in Figure 4, the simulation model uses the FOC control due to its popularity in PMSM control. FOC involves transforming the three-phase stator currents into a d-q axis rotating reference frame, allowing for independent control of torque and flux. This method provides precise control of motor speed and torque, improving overall system efficiency and dynamic performance.

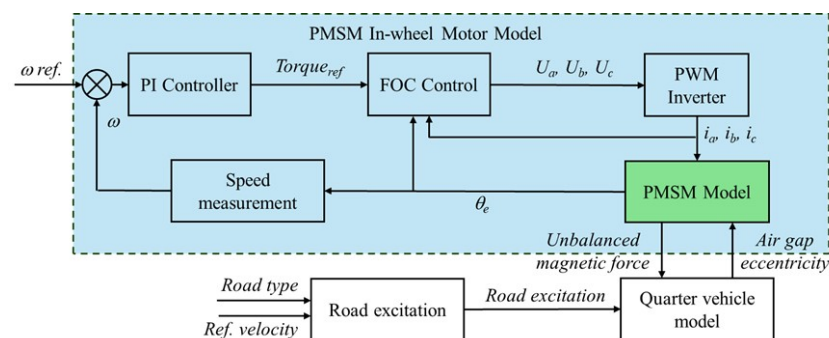


Figure 4. Block diagram of the proposed model.

3.1. Healthy Model Validation

To validate the reliability of the constructed PMSM motor model, the authors conducted a comparative analysis between simulation data and real-world experimental data collected from a physical PMSM system operating under normal conditions [62,63]. This validation approach is essential to ensure that the model accurately captures the baseline behavior of the motor before introducing fault scenarios such as eccentricity. The dataset

provides synchronized measurements of the motor operating variables, including motor speed, electromagnetic torque, battery voltage, battery current, and control signals, thereby serving as a reliable benchmark for model validation.

To ensure a consistent comparison, the simulation was performed under the same operating conditions as those recorded during the experiments. The simulated motor speed and electromagnetic torque were directly compared with the corresponding experimental measurements. The accuracy of the proposed model was quantitatively evaluated using two statistical error metrics, namely the Mean Absolute Error (MAE) and the normalized Mean Absolute Error (nMAE). The MAE represents the average absolute deviation between the simulated and experimental data, while the nMAE normalizes the MAE based on the range of the experimental data, allowing the error to be expressed as a percentage. These metrics are calculated as follows:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_{sim,i} - y_{exp,i}| \quad (17)$$

$$nMAE = \frac{MAE}{y_{max} - y_{min}} \times 100\% \quad (18)$$

where $y_{sim,i}$ and $y_{exp,i}$ denote the simulated and experimental values at the i -th sample, respectively; N is the total number of samples; and y_{max} and y_{min} are the maximum and minimum values of the experimental data.

As shown in Figure 5, the simulated torque closely follows the experimental torque profile throughout the entire operating range, demonstrating that the proposed model successfully captures the dynamic characteristics of the in-wheel motor. The calculated error metrics yield an MAE of 10.262 Nm and an nMAE of 7.762%, indicating that the average simulation error corresponds to only approximately 7.8% of the experimental data range. These results demonstrate good agreement between the simulated and experimental data and confirm the proposed model's ability to reproduce the motor's actual torque characteristics accurately.

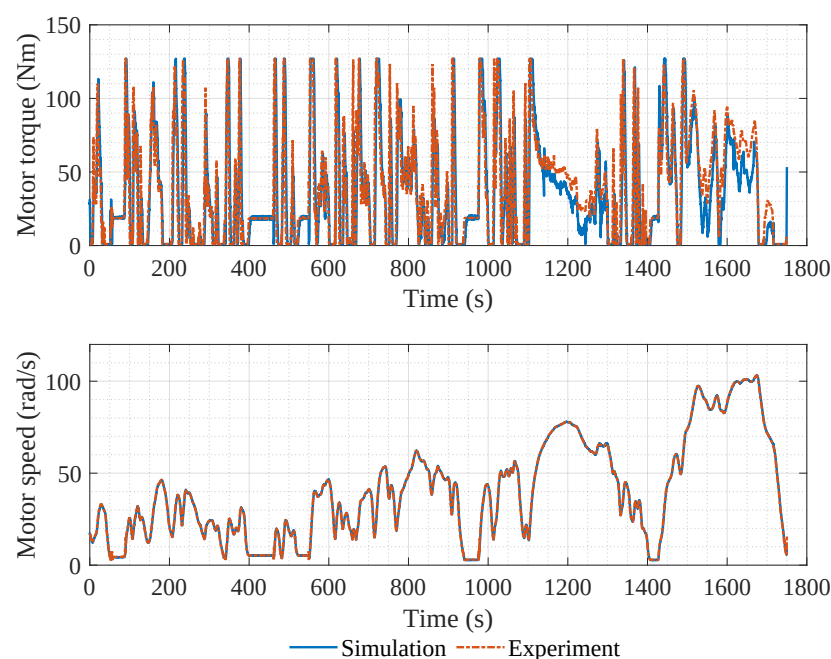


Figure 5. Comparison between simulation results and experimental data.

Based on the validation results, the developed model is considered sufficiently accurate and reliable for subsequent investigations. Therefore, it is employed in the following sections to analyze the influence of different road surface conditions and wheel eccentricity levels on the dynamic performance of the in-wheel motor.

3.2. Effects of Road Surface Excitation on Eccentricity

To investigate the electromechanical coupling behavior of an in-wheel PMSM under both test-bench conditions (without road excitation) and realistic operating conditions (with different road-induced inputs) across different eccentricity cases, this study adopts input parameters representative of an electric SUV equipped with in-wheel PMSMs. The key parameters of the main components used in the simulation model are summarized in Appendix A Table A2.

The eccentricity levels of 10%, 20%, and 30% are selected as representative fault severities corresponding to the progression from incipient to moderate mixed-eccentricity conditions. Previous studies have reported that an air-gap eccentricity of approximately 10% is generally regarded by motor manufacturers and users as the upper limit for acceptable operation [64]. The corresponding eccentricity levels are summarized in Table 1. For all investigated fault severities, the ratio between SE and DE is maintained at 1:2. This ratio is not intended to represent a universal fault composition but is adopted as a representative mixed-eccentricity scenario for in-wheel motors. Maintaining a constant SE–DE ratio ensures that comparisons among different eccentricity levels reflect only the influence of increasing overall eccentricity severity, without introducing additional variations in the relative contributions of the static and dynamic components. A dynamic-dominant composition is selected to reflect the operating characteristics of in-wheel motors, which are continuously subjected to road-induced vibration [48].

Table 1. Definitions of motor eccentricity levels.

Eccentricity Level	Parameters
10% Eccentricity	$e_s = 0.05 \text{ mm}$
	$e_d = 0.10 \text{ mm}$
20% Eccentricity	$e_s = 0.10 \text{ mm}$
	$e_d = 0.20 \text{ mm}$
30% Eccentricity	$e_s = 0.15 \text{ mm}$
	$e_d = 0.30 \text{ mm}$

As the eccentricity level increases, the amplitude of air-gap fluctuations rises markedly. In particular, the 30% eccentricity case exhibits the largest peak-to-peak variations and pronounced irregular oscillations, reflecting a highly non-uniform air-gap distribution. This behavior is attributed to the intensification of unbalanced magnetic pull resulting from air-gap asymmetry, which enhances electromagnetic force harmonics acting on the rotor. According to the electromechanical model described by Equations (12)–(14), the instantaneous air-gap length is jointly determined by the static eccentricity, dynamic eccentricity, and road-induced vertical displacement. The mixed eccentricity severity is defined according to Equation (2). The resulting air-gap variations under different road conditions are presented in Figure 6.

Under the no-road-effect condition (Figure 6a), the air-gap variation remains relatively regular and quasi-periodic, mainly governed by electromagnetic effects. When road excitation is introduced (road class B, Figure 6b), the air-gap response becomes more complex, with increased fluctuation amplitude due to the coupling between road-induced mechani-

cal vibrations and electromagnetic forces. This coupling effect is further aggravated under road class C (Figure 6c), where road-induced excitation produces an additional increase in effective eccentricity compared to no-road effect. It ranges from approximately 10% to 16%, corresponding to the motor eccentricity levels increasing from 10% to 30%, leading to the most severe and irregular air-gap variations.

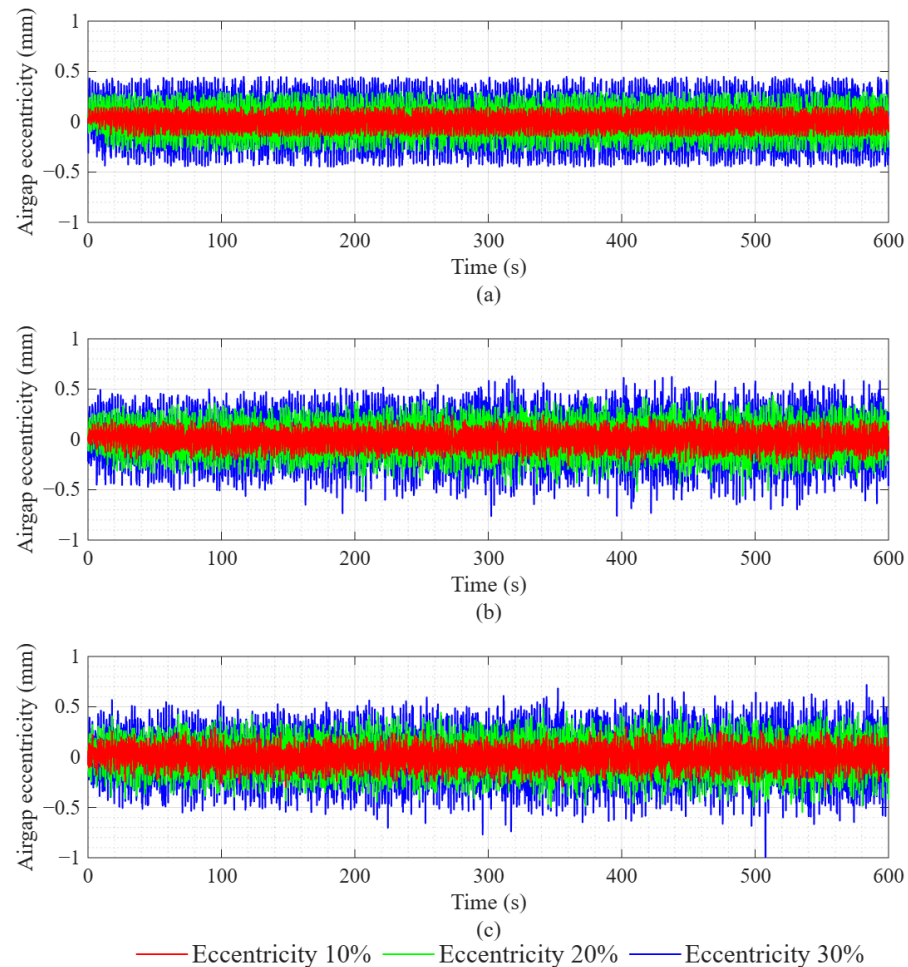


Figure 6. The effect of road surface on the change in the motor air-gap eccentricity. (a) No-road effect; (b) road class B; (c) road class C.

Overall, the results demonstrate that road-induced mechanical disturbances significantly amplify the influence of rotor eccentricity on air-gap dynamics, particularly in in-wheel motor configurations directly exposed to road excitations. From a diagnostic standpoint, the monotonic increase in air-gap fluctuation amplitude with eccentricity level confirms the high sensitivity of air-gap-related signals to eccentricity faults. Nevertheless, under harsh road conditions, strong mechanical excitations may obscure electromagnetic fault signatures, underscoring the need for robust signal processing and feature extraction methods for reliable eccentricity diagnosis in real driving environments.

The unbalanced magnetic force of the rotor in the vertical direction based on Equations (8)–(11) under motor mix eccentricity of 10%, 20% and 30% for three operating conditions is shown in Figure 7.

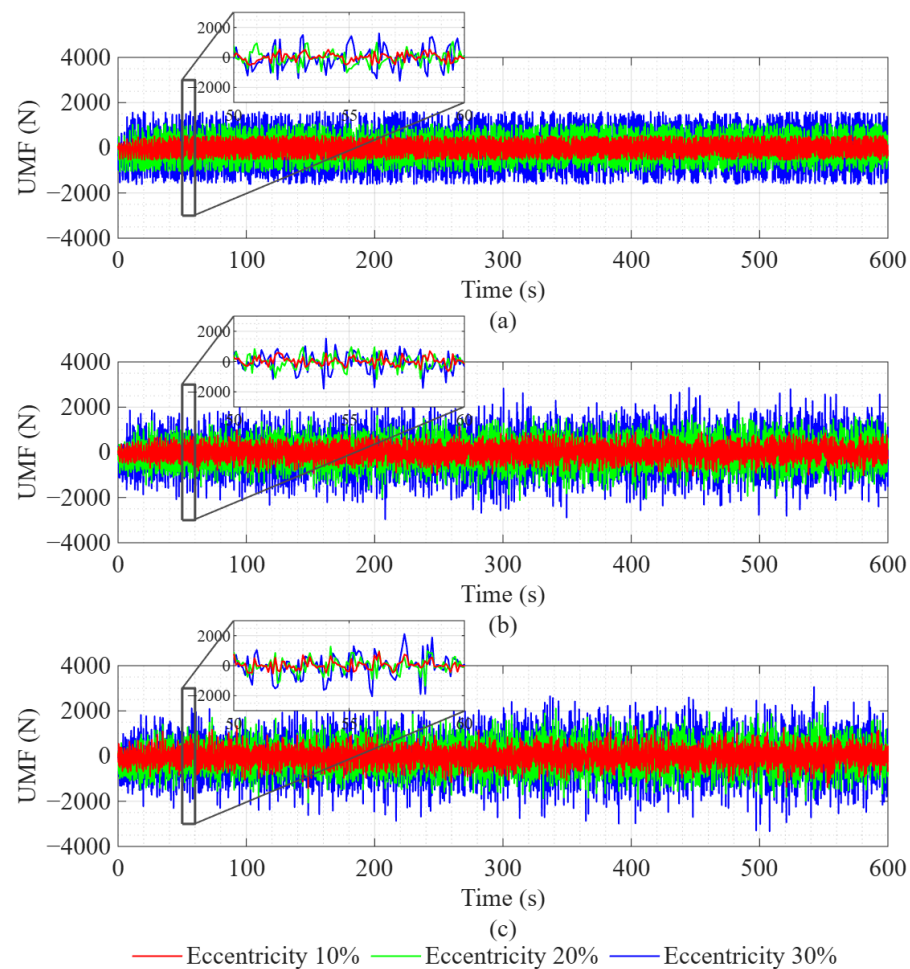


Figure 7. UMF under different mixed eccentricity conditions. (a) No-road effect; (b) road class B; (c) road class C.

The results clearly demonstrate that UMF is jointly influenced by rotor eccentricity and road-induced mechanical excitation. As the eccentricity level increases from 10% to 30%, both the force magnitude and its temporal fluctuation increase monotonically under all operating conditions. Under the no-road condition, the maximum UMF rises from approximately 541 N at 10% eccentricity to 1624 N at 30% eccentricity. When road class C excitation is introduced, the maximum UMF further reaches approximately 4004 N, demonstrating that road vibration considerably intensifies the electromagnetic force response. These observations confirm the strong electromechanical interaction between air-gap variation and magnetic force generation in in-wheel PMSMs.

Without road excitation, the UMF waveform remains relatively regular and quasi-periodic, indicating that the force response is mainly governed by electromagnetic effects. In contrast, the introduction of road class B and road class C excitation produces increasingly complex force variations with noticeably larger oscillation amplitudes. For example, at 10% eccentricity, the maximum UMF under road class C is approximately 2.5 times higher than that in the no-road condition, indicating that vertical road excitation significantly strengthens the influence of rotor eccentricity on the magnetic force response. However, the influence of road excitation must be carefully considered to ensure robust fault detection under real driving conditions.

As discussed in the previous section, current signals are among the most commonly used measurements for fault identification during operation. Accordingly, Figure 8 shows the time evolution of the q -axis current under the considered mixed eccentricity and road conditions. When the motor operates under eccentricity conditions across all road classes,

the resulting torque ripple is compensated by the FOC controller, leading to increased oscillations in i_q . At the operating point corresponding to 80 km/h, the mean value of i_q in the healthy (non-eccentric) condition remains approximately 34.8 A, with only minor fluctuation—about 5.7% without road excitation and up to 7.9% on class C road. In contrast, as eccentricity severity increases, the current variability rises markedly, reaching about 20.3% without road excitation and 24.47% on class C road. These results further indicate that road-induced excitation can substantially amplify eccentricity-related effects and increase the oscillatory content of the motor current signal.

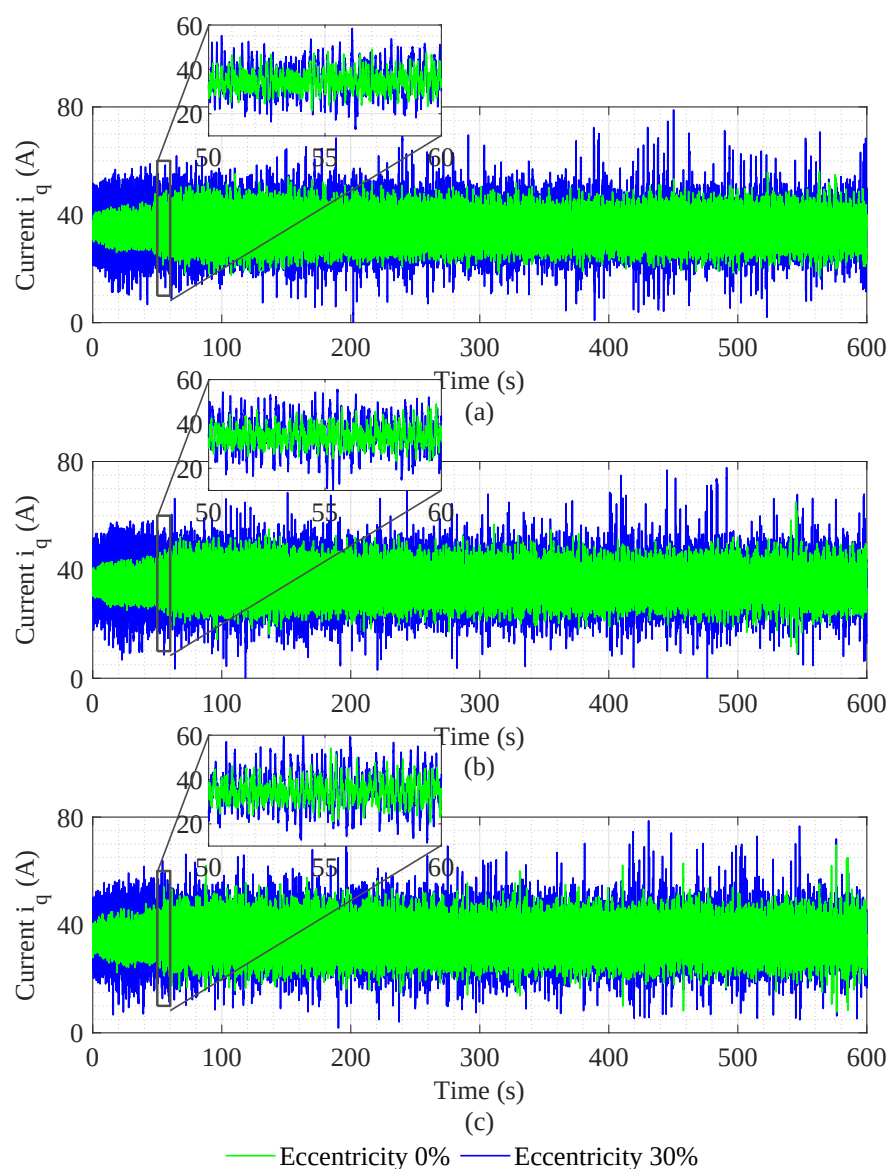


Figure 8. q-axis current under different mixed eccentricity conditions. (a) No-road effect; (b) road class B; (c) road class C.

Since the electromagnetic torque is proportional to the current, as indicated in Equation (6), this study employs the normalized torque-ripple current index (nTRCI) as a surrogate for torque ripple—an indicator commonly used in prior research to assess eccentricity severity. The proposed nTRCI is not intended to replace established current-based diagnostic methods such as MCSA, current RMS, THD, or higher-order statistical indices, but rather serves as a time-domain indicator to evaluate the observability of eccentricity-induced torque-ripple modulation in the q-axis current of an FOC in-wheel PMSM. The

comparison of representative current-based diagnostic indicators and the proposed nTRCI is indicated in Table 2. The novelty of this study lies in linking road-induced excitation, rotor–stator displacement, air-gap eccentricity, UMF, torque ripple, and the resulting q -axis current modulation within a coupled electromechanical framework. Since the q -axis current directly relates to torque production under FOC, its normalized ripple provides a physically meaningful indicator of eccentricity-induced disturbances, making nTRCI a control-observable metric for analyzing road-amplified eccentricity effects rather than a replacement for conventional diagnostic methods.

Table 2. Qualitative comparison of representative current-based diagnostic indicators and the proposed nTRCI.

Diagnostic Indicator	Primary Characteristic	Relation to This Study
MCSA	Frequency-domain analysis of characteristic fault harmonics [25,65].	This study focuses on continuous q -axis current modulation rather than harmonic sideband analysis.
Current RMS/THD	Global indicators describing current magnitude and harmonic distortion [65].	Useful for overall current monitoring but not specifically intended to quantify torque-ripple modulation.
Kurtosis/Skewness	Statistical indicators for impulsive fault signatures [66].	Primarily intended for impulsive fault detection, whereas eccentricity in this work produces continuous current modulation.
Proposed nTRCI	Normalized q -axis current ripple associated with electromagnetic torque under FOC.	An observable indicator adopted to evaluate road-excitation-amplified eccentricity analysis for in-wheel PMSMs through continuous torque-ripple current modulation.

The normalized torque-ripple current index was computed using a 10-second sliding window with a 1-second step, providing a balance between suppressing transient road-induced spikes and preserving the time-varying trend of current ripple. For each window, the RMS value of the detrended q -axis current was normalized by the absolute mean q -axis current to reduce load dependency. The nTRCI is defined as follows:

$$nTRCI(w) = \frac{\sqrt{\frac{1}{N} \sum_{k=1}^N (i_q(k) - \bar{i}_q(w))^2}}{|\bar{i}_q(w)| + \varepsilon} \times 100\%, \quad (19)$$

where

$nTRCI(w)$ is the normalized torque-ripple current index computed over window w ;

N is the number of samples contained in the sliding window;

$i_q(k)$ is the instantaneous q -axis current at sample k (A);

$\bar{i}_q(w)$ is the mean q -axis current over window w (A);

ε is a small positive regularization constant introduced to prevent numerical singularity when $|\bar{i}_q|$ approaches zero.

The 10 s window does not constitute a 10 s detection latency: the window advances in 1 s steps, producing an updated index every second, and the averaging length is chosen to suppress transient road-induced spikes and expose the slow-degradation trend rather

than to detect an acute event. The window and step are tunable, trading noise robustness against responsiveness.

The time evolution of nTRCI under three motor eccentricity levels is presented in Figure 9, where subplots Figure 9a–c correspond to 10%, 20%, and 30% eccentricity, respectively. For each eccentricity level, different road conditions are compared to assess the influence of road-induced excitation on the q-axis current fluctuation. This indicates that air-gap asymmetry enhances torque-ripple-related current modulation, which is reflected in i_q through the FOC loop.

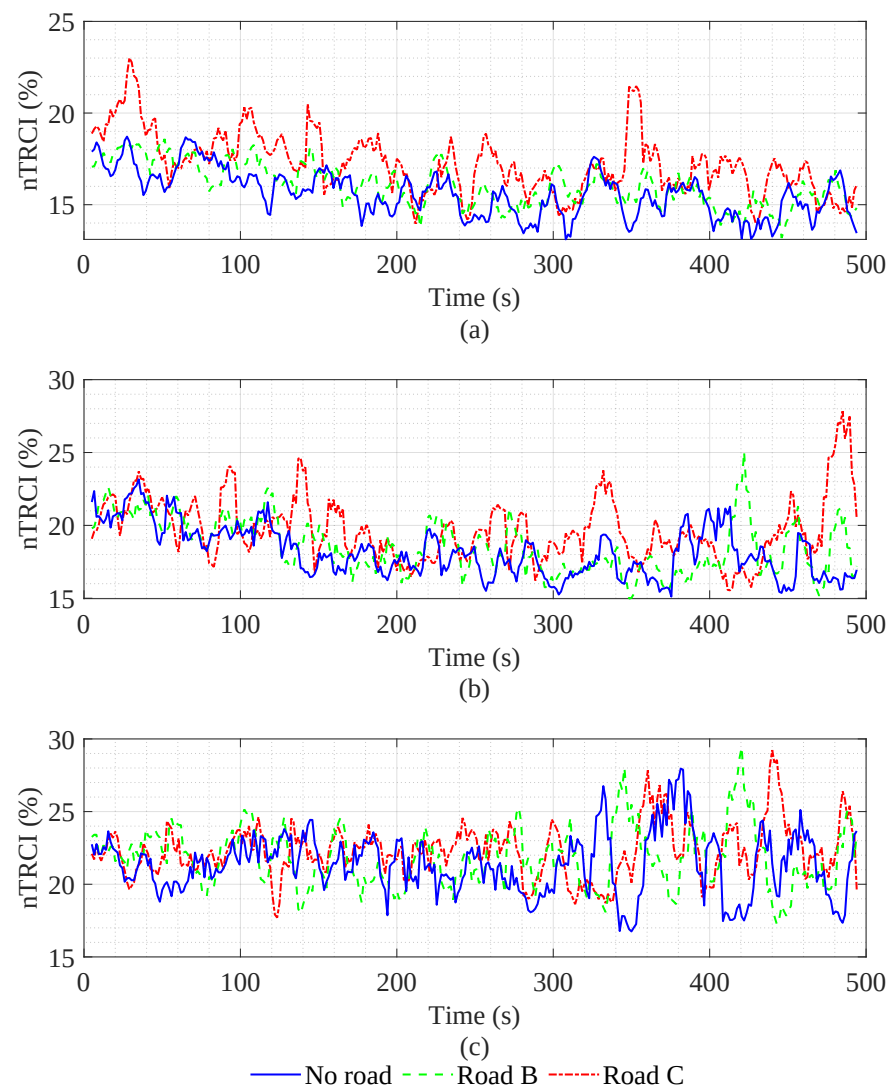


Figure 9. nTRCI under different mixed eccentricity and road conditions. Motor eccentricity: (a) 10%; (b) 20%; (c) 30% .

At 10% eccentricity, Figure 9a shows that nTRCI mainly remains within a relatively narrow range, approximately 14–23%. The road class C condition produces several higher local peaks, whereas the no-road and road class B cases are mostly concentrated around lower values. This suggests that at low eccentricity severity, the intrinsic fault-induced current ripple is still moderate, but rough-road excitation can temporarily amplify the current fluctuation.

At 20% eccentricity, Figure 9b shows a clear upward shift and stronger temporal variation in nTRCI. The index generally lies between approximately 15% and 28%, with road class C producing the most pronounced peaks. This confirms that road-induced vertical

excitation further increases the effective air-gap variation and amplifies the resulting torque-ripple current response.

At 30% eccentricity, Figure 9c indicates that nTRCI remains at a higher level for most of the simulation period. The curves exhibit stronger overlap because the eccentricity-induced current ripple is already dominant, while road excitation adds further stochastic modulation. Therefore, road roughness does not always produce a strictly ordered response at every instant; however, it increases the upper envelope and variability of the index.

These results demonstrate that nTRCI is sensitive to eccentricity severity and can capture the additional amplification effect caused by road excitation. The partial overlap among road conditions indicates that a fixed diagnostic threshold may not be sufficient for in-wheel PMSMs operating under varying road profiles. This overlap occurs because road roughness itself contributes to rotor–stator relative motion and q-axis current modulation, even when the eccentricity severity is unchanged. Therefore, a threshold calibrated under one road condition may become too sensitive on rougher roads, leading to false alarms, or insufficiently sensitive on smoother roads, delaying early fault detection. The threshold can be scheduled according to an estimated road-excitation intensity, using signals such as vertical acceleration, suspension deflection, or wheel-speed fluctuation. This strategy is proposed as a practical extension and requires calibration in future experimental work. Therefore, road condition or vertical excitation intensity should be considered when defining abnormality levels based on i_q -derived indicators.

Based on the above results, this paper proposes abnormality levels and the corresponding implications for other drivetrain components, thereby indicating the inspection needs required to prevent reduced component lifetime and compromised vehicle operating stability. These recommendations are summarized in Table 3. The healthy case with no imposed eccentricity was used as the Normal baseline. The imposed eccentricity levels of 10%, 20%, and 30% were then interpreted as Minor, Moderate, and High abnormality levels, respectively, because they represent increasing levels of prescribed air-gap eccentricity in the simulation model. The numerical boundaries between adjacent classes were determined from the midpoints between the representative nTRCI values of neighboring eccentricity levels.

Table 3. Anomaly levels based on nTRCI.

Eccentricity	0%	10%	20%	30%
No-road effect	Normal	Minor	Moderate	High
Road class B	Normal	Minor	Moderate	High
Road class C	Normal	Moderate	High	High

Overall, the combined effect of rotor eccentricity and poor road conditions leads to the highest torque-ripple levels, degrading torque quality, increasing vibration, and potentially compromising the durability of the drivetrain. From a diagnostic perspective, the relationship between nTRCI and eccentricity level confirms that motor current is a sensitive indicator with strong potential for detecting and quantifying rotor eccentricity faults in in-wheel PMSM systems.

Under road excitation, especially on poor road conditions, mechanical disturbances further amplify air-gap variation, UMF, and torque ripple. Nevertheless, the consistently increasing trend with eccentricity confirms the robustness of the proposed air-gap-UMF-torque-ripple diagnostic chain for rotor eccentricity in in-wheel PMSMs.

4. Conclusions and Future Work

This study developed a coupled electromechanical simulation framework for investigating road-excitation-amplified eccentricity in in-wheel PMSMs and its observability through the q-axis current. By combining a road-induced vertical dynamics model, an air-gap eccentricity model, a UMF formulation, and an FOC PMSM model, the study clarified the propagation path from road roughness to rotor–stator relative displacement, air-gap modulation, UMF, torque ripple, and current fluctuation. The numerical results indicate that increasing road roughness intensifies the eccentricity-related electromagnetic response and produces observable modulation in the q-axis current. The proposed nTRCI therefore provides an indicator for assessing the observability of eccentricity-induced torque-ripple effects using signals that are already available in standard motor-drive control systems.

The present study should be interpreted as a simulation-based mechanism analysis rather than a fully field-validated diagnostic method. The electromechanical model was validated against dynamometer measurements under healthy operating conditions, while validation under seeded eccentricity faults remains an essential next step. Accordingly, the proposed nTRCI is not intended as a field-calibrated diagnostic threshold at this stage, but as an indicator demonstrating the current observability of eccentricity-induced modulation. Because eccentricity is generally a progressive mechanical degradation, the index is more suitable for condition monitoring and prognostics than for safety-critical protection, which is typically handled by fast inverter and vehicle-level protection functions.

Several issues should be addressed before field deployment. Although mean-current normalization reduces the direct influence of load level, practical implementation will require operating-point-aware or adaptive thresholds because vehicle speed, torque demand, road-excitation intensity, and eccentricity-related harmonics can all affect the q-axis current response. Thermal effects should also be considered, since variations in winding and bearing temperature may influence resistance, inductance, flux linkage, and mechanical stiffness. Future work will therefore focus on experimental validation under seeded eccentricity faults, variable-speed and variable-load conditions, regenerative braking, additional ISO road classes, and transient road events such as potholes and speed bumps. Further extensions to interior PMSMs, axial-flux PMSMs, switched-reluctance machines, and dual-rotor in-wheel motors are also planned, together with long-term degradation studies for remaining-useful-life prediction.

Author Contributions: Conceptualization, Q.T.N. and V.N.L.; Methodology, Q.T.N. and A.D.N.; Software, Q.T.N., A.D.N. and V.H.N.; Validation, Q.T.N., A.D.N. and V.H.N.; Formal Analysis, A.D.N. and V.H.N.; Investigation, Q.T.N. and V.N.L.; Resources, V.I.; Writing—Original Draft Preparation, Q.T.N.; Writing—Review and Editing, Q.T.N. and V.N.L.; Visualization, Q.T.N.; Supervision, V.I.; Project Administration, V.I.; Funding Acquisition, V.I. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the European Union’s Horizon Europe research and innovation programme through the project Collaborative Development Framework for Electric Software-Defined Vehicles (CODE4EV), under Grant Agreement No. 101192739. Disclaimer: Funded by the European Union. Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or CINEA. Neither the European Union nor the granting authority can be held responsible for them.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
PMSM	Permanent Magnet Synchronous Motor
IWM	In-Wheel Motor
SE	Static Eccentricity
DE	Dynamic Eccentricity
ME	Mixed Eccentricity
UMF	Unbalanced Magnetic Force
FOC	Field-Oriented Control
MCSA	Motor Current Signature Analysis
RMS	Root-Mean-Square Error
MAE	Mean Absolute Error
nMAE	Normalized Mean Absolute Error
THD	Total Harmonic Distortion
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
SVM	Support Vector Machine
PINN	Physics-Informed Neural Network
ISO	International Organization for Standardization
nTRCI	Normalized Torque-Ripple Current Index
PSD	Power Spectral Density

Appendix A

Table A1. Road roughness classification standard [46].

Roughness Level	$G_d(n_0)$
A	16×10^{-6}
B	64×10^{-6}
C	256×10^{-6}
D	1024×10^{-6}
E	4096×10^{-6}
F	$16,384 \times 10^{-6}$
G	$65,536 \times 10^{-6}$
H	$262,144 \times 10^{-6}$

Table A2. Parameters of the in-wheel electric vehicle model.

Expression	Symbol	Value
Parameters of the IWM Electric Vehicle		
Body mass (kg)	m_b	400
Rotor and wheel mass (kg)	m_r	31.6
Stator mass (kg)	m_s	38.2
Suspension stiffness (N/m)	k_s	30,000
Suspension damping (Ns/m)	c_s	2000
Tire stiffness (N/m)	k_t	250,000
Tire damping (Ns/m)	c_t	360
Equivalent bearing stiffness (N/m)	k_b	8,000,000
Wheel radius (m)	r_d	0.371
Rotor rotational inertia (kg·m ²)	J	0.17
Maximum motor torque (Nm)	T_{max}	1500

Table A2. Cont.

Expression	Symbol	Value
Parameters of the In-Wheel PMSM		
Maximum current (A)	I_{max}	600
Nominal q -axis inductance (H)	L_q	6×10^{-5}
Nominal d -axis inductance (H)	L_d	6×10^{-5}
Stator resistance (Ω)	R_s	0.03
Magnetic remanence (T)	B_r	0.7
Nominal air-gap length (mm)	g_0	1.5
Number of pole pairs	N_p	32
Vacuum permeability (H/m)	μ_0	$4\pi \times 10^{-7}$

References

1. Tao, Y.; Wang, X.; Zhang, L.; Bao, X.; Xue, H.; Yue, H.; Feng, H.; Yang, D. Fault Diagnosis of In-Wheel Motors Used in Electric Vehicles: State of the Art, Challenges, and Future Directions. *Machines* **2025**, *13*, 711. <https://doi.org/10.3390/machines13080711>.
2. Deepak, K.; Frikha, M.A.; Benômar, Y.; El Baghdadi, M.; Hegazy, O. In-Wheel Motor Drive Systems for Electric Vehicles: State of the Art, Challenges, and Future Trends. *Energies* **2023**, *16*, 3121. <https://doi.org/10.3390/en16073121>.
3. Xu, X.; Wang, M.; Xiao, P.; Ding, J.; Zhang, X. In-Wheel Motor Control System for Four-Wheel Drive Electric Vehicle Based on CR-GWO-PID Control. *Sensors* **2023**, *23*, 8311. <https://doi.org/10.3390/s23198311>.
4. Chris, B.B. Making the case for in-wheel motors SAE-MA-06747. In *Sustainability, Automated and Autonomous Systems*; SAE: Warrendale, PA, USA, 2021. Available online: <https://www.sae.org/articles/making-case-wheel-motors-sae-ma-06747> (accessed on 15 December 2025).
5. Wu, P.; Luo, R.; Yu, Z.; Hou, Z. Evaluation of the unsprung mass effect on ride comfort of in-wheel motor driving vehicles. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2025**, *239*, 5336–5352. <https://doi.org/10.1177/09544070241288615>.
6. Nie, S.; Zhuang, Y.; Chen, F.; Wang, Y.; Liu, S. A method to eliminate unsprung adverse effect of in-wheel motor-driven vehicles. *Journal Low. Freq. Noise Vib. Act. Control* **2018**, *37*, 955–976. <https://doi.org/10.1177/1461348418767096>.
7. Anderson, M.; Harty, D. Unsprung Mass with In-Wheel Motors—Myths and Realities. *AVEC 10* **2010**, 261–266. Available online: <https://api.semanticscholar.org/CorpusID:197867400> (accessed on 18 December 2025).
8. Alluhydan, K.; Amer, Y.A.; EL-Sayed, A.T.; Agwa, M.M. Stability and Control of Car Dynamics with a Quarter Model via a Novel Simple Harmonic Hump under External Force. *Mathematics* **2024**, *12*, 3046. <https://doi.org/10.3390/math12193046>.
9. van Schalkwyk, D.J.; Kamper, M.J. Effect of Hub Motor Mass on Stability and Comfort of Electric Vehicles. In Proceedings of the IEEE Vehicle Power and Propulsion Conference, Windsor, UK, 6–8 September 2006; pp. 1–6. <https://doi.org/10.1109/VPPC.2006.364297>.
10. Zhao, P.; Fan, Z.M. Design, modeling, and research on vertical performance of a drive system with in-wheel motor as dynamic vibration absorber. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2022**, *237*, 862–877. <https://doi.org/10.1177/09544070221078360>.
11. Shao, X.; Naghdy, F.; Du, H.; Qin, Y. Coupling effect between road excitation and an in-wheel switched reluctance motor on vehicle ride comfort and active suspension control. *J. Sound. Vib.* **2019**, *443*, 683–702. <https://doi.org/10.1016/j.jsv.2018.12.012>.
12. Feng, G.; Li, S.; Wang, X. Nonlinear Vibration Characteristic Analysis of Electric Vehicle–Road Coupling System. *Int. J. Mech. Syst. Dyn.* **2026**, *6*, 267–281. <https://doi.org/10.1002/msd2.70064>.
13. Li, L.; Kang, S.; Deng, J. Design and parameter optimization of a new type in-wheel motor drive electric vehicle vibration reduction system. *J. Vibroeng.* **2023**, *26*, 401–413. <https://doi.org/10.21595/jve.2023.23551>.
14. Petryna, J.; Duda, A.; Sułowicz, M. Eccentricity in Induction Machines—A Useful Tool for Assessing Its Level. *Energies* **2021**, *14*, 1976. <https://doi.org/10.3390/en14071976>.
15. Jombo, G.; Zhang, Y. Fault Detection and Isolation in Electric Vehicle Powertrain. In *Modern Automotive Electrical Systems*; Asef, P., Padmanaban, S., Lapthorn, A., Eds.; John Wiley and Sons: Hoboken, NJ, USA, 2022. <https://doi.org/10.1002/9781119801078.ch5>.
16. Zhao, Z.; Taghavifar, H.; Du, H.; Qin, Y.; Dong, M.; Gu, L. In-Wheel Motor Vibration Control for Distributed-Driven Electric Vehicles: A Review. *IEEE Trans. Transp. Electr.* **2021**, *7*, 2864–2888. <https://doi.org/10.1109/TTE.2021.3074970>.
17. Li, H.; Zhu, Z.-Q.; Azar, Z.; Clark, R.; Wu, Z. Fault Detection of Permanent Magnet Synchronous Machines: An Overview. *Energies* **2025**, *18*, 2864–2888. <https://doi.org/10.3390/en18030534>.
18. Huang, F.; Chen, C.; Sun, X.; Wang, Z.; Fu, H. Dynamic behavior of permanent magnet synchronous motor rotor bending fault. *Measurement* **2025**, *256*, 118123. <https://doi.org/10.1016/j.measurement.2025.118123>.
19. Li, Z.; Song, X.; Chen, X.; Xue, H. Dynamic Characteristics Analysis of the Hub Direct Drive-Air Suspension System from Vertical and Longitudinal Directions. *Shock Vib.* **2021**, *11*, 8891860. <https://doi.org/10.1155/2021/8891860>.

20. Pooja, V.; Vikas, P.; Sushma, S.; Prerana, D.; Deepika, S. Bearing Fault Analysis of Permanent Magnet Synchronous Motor(PMSM) using Current Signature Analysis. *Int. Res. J. Eng. Technol. (IRJET)* **2017**, *4*, 410–415.
21. Adil, U.; Nikhil, T.D.; Bharat, S.R. Stator Winding Faults investigation in Permanent Magnet Synchronous Motor using Motor Signatures: Part I. In Proceedings of the 2019 International Conference on Electrical Drives & Power Electronics (EDPE), The High Tatras, Slovakia, 24–26 September 2019. <https://doi.org/10.1109/EDPE.2019.8883929>.
22. Chen, Y.; Liang, S.; Li, W.; Liang, H.; Wang, C. Faults and Diagnosis Methods of Permanent Magnet Synchronous Motors: A Review. *Appl. Sci.* **2019**, *9*, 2116. <https://doi.org/10.3390/app9102116>.
23. Biček, M.; Gotovac, G.; Miljavec, D.; Zupan, S. Mechanical Failure Mode Causes of In-Wheel Motors. *Stroj. Vestn.-J. Mech. Eng.* **2015**, *61*, 74–85. <https://doi.org/10.5545/sv-jme.2014.2022>.
24. Gherabi, Z.; Benouzza, N.; Toumi, D.; Bendiabdellah, A. Eccentricity Fault diagnosis in PMSM using Motor Current Signature Analysis. In Proceedings of the 2019 International Aegean Conference on Electrical Machines and Power Electronics (ACEMP) & 2019 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM), Istanbul, Turkey, 27–29 August 2019; pp. 205–210. <https://doi.org/10.1109/ACEMP-OPTIM44294.2019.9007164>.
25. Youngsu, K.; Younghun, L.; Jaewook, O.; Jongchan, P.; Hongsuk, C.; Namsu, K. Current signature identification and analysis for demagnetization fault diagnosis of permanent magnet synchronous motors. *Mech. Syst. Signal Process.* **2024**, *214*, 111377. <https://doi.org/10.1016/j.ymssp.2024.111377>.
26. Hong, J.; Sang, B.L.; Christian, K.; Anton, H. Detection of airgap eccentricity for permanent magnet synchronous motors based on the d-axis inductance. In Proceedings of the 8th IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives, Bologna, Italy, 5–8 September 2021; pp. 378–384. <https://doi.org/10.1109/DEMPED.2011.6063651>.
27. Yu, Y.; Gao, H.; Zhou, S.; Pan, Y.; Zhang, K.; Liu, P.; Yang, H.; Zhao, Z.; Madyira, D.M. Rotor Faults Diagnosis in PMSMs Based on Branch Current Analysis and Machine Learning. *Actuators* **2023**, *12*, 145. <https://doi.org/10.3390/act12040145>.
28. Li, Z.; Wu, Q.; Yang, S.; Chen, X. Diagnosis of rotor demagnetization and eccentricity faults for IPMSM based on deep CNN and image recognition. *Complex Intell. Syst.* **2022**, *8*, 5469–5488. <https://doi.org/10.1007/s40747-022-00764-z>.
29. Maëva, G.; Panagiotis, A.; Jose, P.; Jose, A.A.D.; Konstantinos, N.G. Efficiency Assessment of Induction Motors Operating Under Different Faulty Conditions. *IEEE Trans. Ind. Electron.* **2019**, *66*, 8072–8081. <https://doi.org/10.1109/TIE.2018.2885719>.
30. Chu, K.S.K.; Chew, K.W.; Chang, Y.C.; Morris, S.; Hoon, Y.; Chen, C. Eccentricity Fault Diagnosis System in Three-Phase Permanent Magnet Synchronous Motor (PMSM) Based on the Deep Learning Approach. *Sensors* **2025**, *25*, 7416. <https://doi.org/10.3390/s25247416>.
31. Kumar, N.B.; Babu, A.R.V.; Kumar, M.B.A.; Kumar, T.S. Hybrid digital twin-based fault diagnosis framework for PMSMs in electric vehicle applications. *Frankl. Open* **2025**, *12*, 100328. <https://doi.org/10.1016/j.fraope.2025.100328>.
32. Valiyil, R.; R, B.; Nair, A.; Puthiyapurayil, S.; Ravi, R. Enabled Digital Twin of the Traction Motor of an Electric Vehicle. In Proceedings of the WCX SAE World Congress Experience, Detroit, MI, USA, 8 April 2025. <https://doi.org/10.4271/2025-01-8564>.
33. Adegbite, T.; Refaat, S.S.; Farrag, M.; Mohammed, A. Embedded AI-Enabled Fault Detection System for Electric Vehicle Powertrains. In Proceedings of the 2025 IEEE 4th Industrial Electronics Society Annual On-Line Conference (ONCON), Online, 11–13 December 2025. <https://doi.org/10.1109/ONCON68412.2025.11384182>.
34. Annapareddy, S.R. Edge AI for Real-Time Fault Detection in Embedded Systems. *Int. J. Emerg. Trends Comput. Sci. Inf. Technol.* **2025**, *2025*, 235–238. <https://doi.org/10.56472/ICCSAIML25-129>.
35. Liu, P. Research on motor fault recognition based on multi-sensor fusion. *Internet Technol. Lett.* **2025**, *8*, e425. <https://doi.org/10.1002/itl2.425>.
36. Pérez, R.; Cros, J.; Picard, M. Real-Time Modeling of Static, Dynamic and Mixed Eccentricity in Permanent Magnet Synchronous Machines. *Machines* **2025**, *13*, 120. <https://doi.org/10.3390/machines13020120>.
37. Liu, Z.; Zhang, P.; He, S.; Huang, J. A Review of Modeling and Diagnostic Techniques for Eccentricity Fault in Electric Machines. *Energies* **2021**, *14*, 4296. <https://doi.org/10.3390/en14144296>.
38. Terron-Santiago, C.; Martinez-Roman, J.; Puche-Panadero, R.; Sopena-Bano, A.; Burriel-Valencia, J.; Pineda-Sanchez, M. Analytical Model of Eccentric Induction Machines Using the Conformal Winding Tensor Approach. *Sensors* **2022**, *22*, 3150. <https://doi.org/10.3390/s22093150>.
39. Zuo, S.; Lin, F.; Deng, W. Impact of rotor eccentricity on electromagnetic vibration and noise of permanent magnet synchronous motor. *J. Vibroeng.* **2018**, *20*, 923–935. <https://doi.org/10.21595/jve.2017.18436>.
40. Kartal, E.T.; Arabul, F.K. Effects of air gap eccentricity on different rotor structures for PMSM in electric vehicles. *Sci. Rep.* **2024**, *14*, 17335. <https://doi.org/10.1038/s41598-024-68632-z>.
41. Wang, S. Effect of Air Gap Eccentricity on the Torque and Losses of Bulb Tubular Turbine Generators. *Int. J. Eng. Adv.* **2025**, *2*, 80–90. <https://doi.org/10.71222/q6svq425>.
42. Wang, D.; Yang, W.; Yang, J.; Jiang, K.; Zhang, J.; Fu, Y. Research on the vibration characteristics and performance optimization of the rotor-shaft system of an unbalanced permanent magnet synchronous motor. *J. Mech. Sci. Technol.* **2023**, *37*, 4425–4439. <https://doi.org/10.1007/s12206-023-0802-1>.

43. Rao, Y.; Wang, W.; Fu, J.; Cui, P.; Zheng, Z. A Current Residual-Based Mixed Fault Diagnosis and Differentiation of PMSM Servo Systems. *IEEE Trans. Ind. Appl.* **2025**, *61*, 9004–9014. <https://doi.org/10.1109/TIA.2025.3570344>.
44. Rajesh, G.; Sebasthirani, K. Modeling and Control of Permanent Magnet Synchronous Motor Based Electric Vehicle. *Adv. Mech. Eng.* **2025**, *17*, 1–18. <https://doi.org/10.1177/16878132251333015>.
45. Fatimah, J.; Abdulhasan, F.A. Mathematical Model of Permanent Magnet Synchronous Motor. *UTJES* **2022**, *12*, 10–14. [https://doi.org/10.31663/tqujes.12.2.444\(2022\)](https://doi.org/10.31663/tqujes.12.2.444(2022)).
46. Elsherbiny, H.; Szamel, L.; Ahmed, M.K.; Elwany, M.A. High Accuracy Modeling of Permanent Magnet Synchronous Motors Using Finite Element Analysis. *Mathematics* **2022**, *10*, 3880. <https://doi.org/10.3390/math10203880>.
47. Vas, P. *Sensorless Vector and Direct Torque Control*; Oxford University Press: Oxford, UK, 1998. <https://doi.org/10.1093/oso/9780198564652.001.0001>.
48. Zhang, D.; Zhong, C.; Liu, S.; Xu, P.; Tian, Y. Vertical vibration control to the in-wheel-motor electric vehicles with static eccentricity based on a reinforcement learning method. *J. Vib. Control* **2024**, *30*, 1387–1400. <https://doi.org/10.1177/10775463241264047>.
49. Chen, X.; Deng, Z.; Hu, J.; Deng, T. An analytical model of unbalanced magnetic pull for PMSM used in electric vehicle: Numerical and experimental validation. *Int. J. Appl. Electromagn. Mech.* **2017**, *53*, 583–596. <https://doi.org/10.3233/JAE-160121>.
50. Tan, D.; Wu, Y.; Song, F. Impact of road surface roughness and magnetic force on the in-wheel motor magnet gap. *J. Vibroeng.* **2017**, *19*, 6313–6327. <https://doi.org/10.21595/jve.2017.18576>.
51. Meng, X.; Rong, Y.; Ding, R.; Liu, W.; Sun, D.; Wang, R. Research on suppression of negative effects of vibration in in-wheel motor-driven electric vehicles based on DMPC. *Processes* **2025**, *13*, 3081. <https://doi.org/10.3390/pr13103081>.
52. Zhao, Z.; Zhang, L.; Wu, J.; Gu, L.; Li, S. Vertical-Longitudinal Coupling Effect Investigation and System Optimization for a Suspension-In-Wheel-Motor System in Electric Vehicle Applications. *Sustainability* **2023**, *15*, 4168. <https://doi.org/10.3390/su15054168>.
53. Meng, X.; Zhang, Y.; Ding, R.; Liu, W.; Wang, R. Research on unbalanced electromagnetic force under static eccentricity of the wheel hub motor based on BP neural network. *World Electr. Veh. J.* **2025**, *16*, 252. <https://doi.org/10.3390/wevj16050252>.
54. ISO 8608:2016; Mechanical Vibration—Road Surface Profiles—Reporting of Measured Data. ISO: Geneva, Switzerland, 2016.
55. P. Můčka, Simulated Road Profiles According to ISO 8608 in Vibration Analysis. *J. Test. Eval.* **2018**, *46*, 405–418. <https://doi.org/10.1520/JTE20160265>.
56. Loprencipe, G.; Zoccali, P.; Cantisani, G. Effects of vehicular speed on the assessment of pavement road roughness. *Appl. Sci.* **2019**, *9*, 1783. <https://doi.org/10.3390/app9091783>.
57. Loprencipe, G.; Zoccali, P. Use of generated artificial road profiles in road roughness evaluation. *J. Mod. Transp.* **2017**, *25*, 24–33. <https://doi.org/10.1007/s40534-017-0122-1>.
58. Agostinacchio, M.; Ciampa, D.; Olita, S. The vibrations induced by surface irregularities in road pavements – a Matlab approach. *Eur. Transp. Res. Rev.* **2014**, *6*, 267–275. <https://doi.org/10.1007/s12544-013-0127-8>.
59. Xing, J.; Cheng, Z.; Ye, S.; Liu, S.; Lin, J. Road roughness recognition: Feature extraction and speed-adaptive classification based on simulation and real-vehicle tests. *Machines* **2025**, *13*, 391. <https://doi.org/10.3390/machines13050391>.
60. Fu, Y.; Liu, Z.; Jiang, Y.; Leng, Y.; Tang, J.; Wang, R.; Lv, X. Simulation and experiment of the smoothness performance of an electric four-wheeled chassis in hilly and mountainous areas. *Sustainability* **2023**, *15*, 16868. <https://doi.org/10.3390/su152416868>.
61. Liu, J.; Liu, J.; Li, Y.; Wang, G.; Yang, F. Study on Multi-Mode Switching Control Strategy of Active Suspension Based on Road Estimation. *Sensors* **2023**, *23*, 3310. <https://doi.org/10.3390/s23063310>.
62. Bacha, A. Comprehensive Dataset for Fault Detection and Diagnosis in Inverter-Driven PMSM Systems, Zenodo. 2024. Available online: <https://zenodo.org/records/13974503> (accessed on 29 July 2026).
63. Cyrano, V.; Sebastiaan, V.A. Test Results at Ford Lommel Proving Ground ESR 11. Zenodo. 2019. Available online: <https://zenodo.org/records/3263811> (accessed on 29 July 2026).
64. Thomson, W.T.; Barbour, A. On-line current monitoring and application of a finite element method to predict the level of static airgap eccentricity in three-phase induction motors. *IEEE Trans. Energy Convers.* **1998**, *13*, 347–357. <https://doi.org/10.1109/60.736320>.
65. Nandi, S.; Toliyat, H.A.; Li, X. Condition monitoring and fault diagnosis of electrical motors—A review. *IEEE Trans. Energy Convers.* **2005**, *20*, 719–729. <https://doi.org/10.1109/TEC.2005.847955>.
66. Wang, Y.; Xiang, J.; Markert, R.; Liang, M. Spectral kurtosis for fault detection, diagnosis and prognostics of rotating machines: A review with applications. *Mech. Syst. Signal Process.* **2016**, *66–67*, 679–698. <https://doi.org/10.1016/j.ymssp.2015.04.039>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.