



REVIEW ARTICLE

# Advances in prediction methods for wear of high-speed railway wheels: a review and future outlook

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## ARTICLE INFO

Received: 08/06/2026

Revised: 25/08/2026

Accepted: 07/09/2026

Published online: 15/09/2026

## KEYWORDS

High-speed railway  
Numerical simulation  
Wheel wear prediction  
Wheel-rail contact

## ABSTRACT

Wheel wear is a critical degradation mechanism in railway systems, significantly influencing safety, ride comfort, maintenance costs, and lifecycle performance, particularly in high-speed railway (HSR) operations. Accurate prediction of wheel wear evolution remains challenging due to the strong coupling between wheel-rail (WR) contact mechanics, vehicle-track (VT) dynamics, material behavior, and operational variability. This paper provides a comprehensive review and comparative assessment of state-of-the-art wheel wear prediction methods, focusing on their applicability to HSR systems. Existing approaches are systematically categorized into five groups: empirical and semi-empirical models, physics-based contact and wear models, VT-coupled multi-body dynamics (MBD) methods, experimental and measurement-driven approaches, and data-driven or hybrid frameworks. Each category is evaluated in terms of modeling assumptions, input requirements, predictive capability, computational efficiency, and suitability for high-speed conditions. A structured comparison highlights the strengths and limitations of different methodological classes, particularly regarding physical interpretability, scalability, and validation robustness. Key research gaps are identified, including limited integration of wear-fatigue interactions, challenges in cross-condition generalization, and insufficient field-based validation. Finally, emerging directions such as physics-informed data-driven models, real-time monitoring integration, and digital twin frameworks are discussed as promising pathways toward reliable and scalable wheel wear prediction in next-generation railway systems.

## 1. Introduction

High-speed railway (HSR) systems are widely recognized as a cornerstone of sustainable transportation owing to their high capacity, energy efficiency, and operational reliability [1]. Within these systems, the wheel-rail (WR) interface is regarded as a critical mechanical subsystem, as running safety, vehicle stability, ride comfort, noise emission, and infrastructure maintenance costs are directly governed by its performance [2]. Among the degradation mechanisms acting at this interface, wheel wear is identified as a dominant and unavoidable phenomenon, particularly under high-speed, high-load, and long-term operating conditions [3].

As wheel wear progresses, the wheel tread and flange profiles are gradually altered, leading to modifications in WR contact conditions, including contact patch geometry, normal pressure distribution, creepage, and frictional behavior. As a consequence, adverse effects such as increased dynamic interaction forces, reduced hunting stability, elevated noise and vibration levels, accelerated rail wear, and a higher risk of rolling contact fatigue (RCF) are induced. From an operational perspective, frequent wheel reprofiling or replacement is required when excessive wear occurs, resulting in in-

creased maintenance costs and reduced vehicle availability, especially in high-speed networks with limited maintenance windows [4–5].

In HSR operations, wheel wear is further intensified by sustained high speeds, stringent ride comfort requirements, lightweight vehicle structures, and tight tolerances in WR interaction. Therefore, accurate prediction of wheel wear evolution is considered essential not only for maintenance planning but also for the optimization of wheel profiles, material selection, suspension design, and the implementation of predictive maintenance strategies.

Over the past decades, extensive research efforts have been undertaken to investigate and predict wear phenomena in railway systems. However, existing review studies have primarily addressed rail wear, combined WR wear and damage, or numerical modelling of wheel and rail profile wear [6–7]. In contrast, a dedicated and systematic synthesis of wheel wear prediction methods, particularly for HSR applications, remains limited.

Unlike rails, wheels are rotating components that are repeatedly subjected to reprofiling operations and experience complex three-dimensional wear patterns, material inhom-

geneities, thermal loading induced by braking, and continuously evolving contact conditions across tread and flange regions [8]. In addition, the progression of wheel wear is strongly affected by vehicle dynamics, suspension characteristics, traction and braking strategies, and route-specific operational conditions, which fundamentally differ from those governing rail wear behavior [9].

A comprehensive review of wheel wear prediction methods for HSR systems is presented, in which the wheel is explicitly considered as the primary object of analysis. Wear locations and profile evolution on railway wheels including tread wear, flange wear, and hollow wear are systematically addressed, together with wear mechanisms relevant to high-speed operation, such as rolling and sliding wear, creepage-related wear, RCF-associated wear, thermally induced wear due to braking, and environmentally influenced wear. Material-related aspects, including wheel steel grades, hardness evolution, and material-dependent wear behavior, are examined, while the influences of operational and dynamic conditions such as vehicle speed, axle load, suspension characteristics, curve negotiation, traction and braking regimes, and track conditions are analyzed. Emphasis is placed on prediction-oriented methodologies, ranging from physics-based wear models and numerical simulations to experimental and data-driven approaches, rather than purely descriptive or post-failure analyses, in order to support engineering applications including maintenance planning, wheel profile optimization, and digital twin development.

The remainder of this paper is organized as follows. Section 2 describes the characteristics and wear modes of railway wheels. Section 3 provides an overview of wheel wear prediction modeling approaches. Section 4 discusses and analyzes five wheel wear prediction methods and evaluates their applicability to HSR systems. Section 5 summarizes the challenges in wheel wear prediction and outlines future research directions. Finally, Section 6 presents the concluding remarks.

## 2. Wear mechanisms and characteristics of HSR wheels

### 2.1. General characteristics of wheel wear in HSR

Wheel wear in HSR systems is a progressive, multi-mechanism degradation process caused by repeated WR contact under complex mechanical, thermal, and environmental conditions. Compared to conventional railways, HSR requires stricter control of wheel profile geometry and contact stability due to higher speeds and sensitivity to irregularities. Wear results from combined mechanisms such as RCF, abrasion, and adhesion, all governed by contact stress, creepage, and material properties. Small profile deviations can significantly alter contact conditions, accelerating wear. Importantly, wear evolution also affects vehicle dynamics by modifying equivalent conicity, thereby influencing stability and potentially increasing derailment risk. Hence, wheel wear in HSR is not only a maintenance issue but a key factor in ensuring operational safety and dynamic performance.

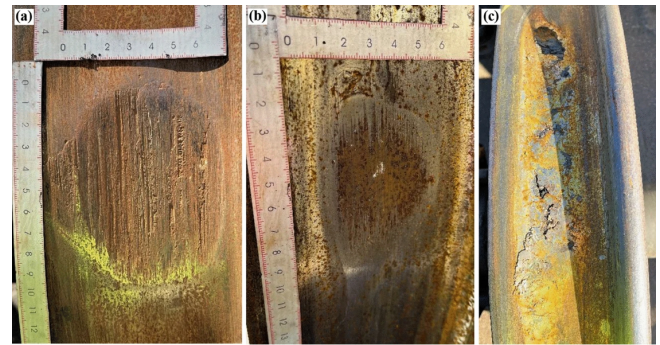


**Figure 1.** Wheel tread damage evolution. (a) Newly formed wheel flat with sharp edges. (b) Wheel flat with rounded edges after repeated WR contact. (c) RCF [11]

Wheel wear is manifested through three-dimensional profile evolution, whereby changes in tread curvature, flange thickness, flange height, and the formation of hollow wear regions are induced. These geometric variations are directly reflected in modifications of WR contact conditions [10]. Wheel flats are generated as a result of wheel sliding on the rail, as shown in Figure 1 [11]. As a result, wheel wear is not regarded as a purely local surface phenomenon but is instead required to be treated as a system-level problem that is strongly coupled with vehicle dynamics and track characteristics.

In HSR systems, wheel wear is typically associated with a lower mass loss rate compared to heavy-haul operations; however, even small geometric deviations can produce disproportionately large effects on system behavior. Slight changes in wheel profile may significantly alter contact geometry and equivalent conicity, thereby affecting hunting stability and increasing dynamic sensitivity. Moreover, these deviations can accelerate RCF by modifying stress distribution at the WR interface, while also contributing to higher noise emission and intensified rail degradation. Consequently, in HSR, the impact of wear is governed less by material loss and more by its influence on contact conditions and dynamic performance.

### 2.2. Classification of wheel wear mechanisms

#### 2.2.1. Rolling and sliding wear due to creepage

Rolling and sliding associated with creepage constitute fundamental mechanisms governing wheel wear. According to the classical rolling-contact theories, the relative motion within the WR contact patch is generally characterized by a combination of adhesion and slip regions rather than by uniform pure rolling. Under idealized conditions, local rolling without slip may occur within part of the contact region; longitudinal, lateral, and spin creepages generated by traction and braking, curving, wheelset yaw, and geometric incompatibilities between WR profiles produce relative tangential motion within the contact patch [12]. Consequently, the contact patch generally contains coupled adhesion and partial-slip regions, and the resulting micro-slip provides a fundamental source of frictional energy dissipation and wear. At the microscale, repeated tangential shearing can promote adhesive and abrasive wear through asperity junction rupture, ploughing, and micro-cutting, thereby contributing to the evolution of wheel tread and flange profiles [13–14].

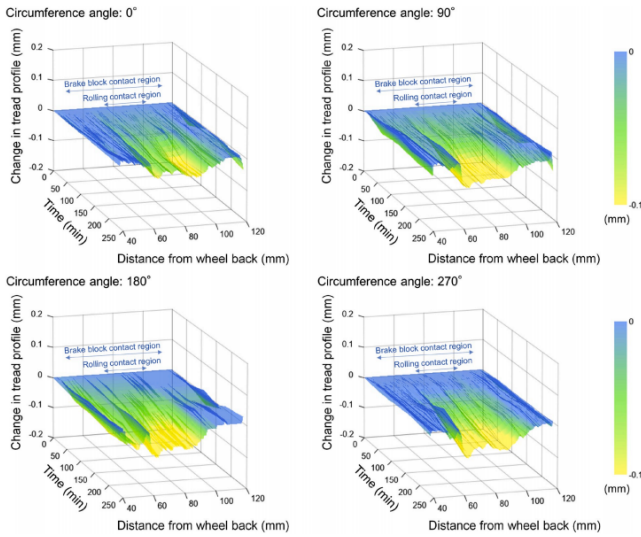


**Figure 2.** Evolution of tread profile deviation from the initial state at four wheel perimeter locations during constant-temperature tests [18]

In HSR operation, creepage-induced wear is strongly affected by operating speed, traction and braking, contact geometry, and friction conditions. Experimental and numerical studies have shown that increasing speed can modify the creep-force-creepage relationship, adhesion level, slip distribution, and contact stress, particularly under low-adhesion conditions [15–16]. Traction and braking can further increase longitudinal creepage and sliding, thereby accelerating tread wear. Under braking, severe sliding and associated frictional heating can substantially increase wear compared with dry rolling conditions [8, 17–18]. In particular, Figure 2 illustrates the evolution of wheel tread wear at different braking-induced temperature levels, highlighting the interaction between sliding and thermal effects.

Lateral and spin creepages are primarily controlled by WR contact geometry, equivalent conicity, and wheelset guidance characteristics. As wheel wear progresses, the contact geometry and equivalent conicity evolve, potentially altering wheelset guidance, dynamic stability, and the distribution of WR contact [19–21]. Thus, wheel wear should not be considered solely as a consequence of creepage; rather, wear-induced profile evolution can modify the contact conditions that subsequently govern further wear, resulting in a coupled wear-dynamics process. Friction conditions also play an important role in wear development. Increased friction generally promotes tangential forces and micro-slip, whereas friction modifiers (FMs) can reduce adhesion-related damage and wear. However, excessive friction reduction may compromise traction and vehicle stability. Experimental investigations have demonstrated that FM effectiveness depends on contact stress, creepage, and application conditions, with appropriate FM formulations reducing WR wear while maintaining adequate adhesion [22–23]. These findings indicate that friction management should be considered together with contact mechanics when evaluating wheel wear under operational conditions.

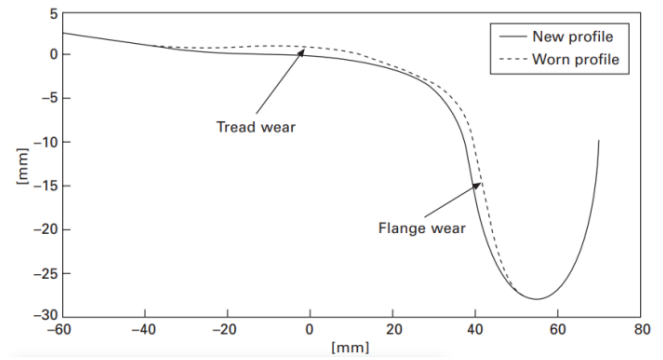


**Figure 3.** Wheel flange and tread wear [29]

From an operational perspective, tread wear is generally associated with rolling and sliding under moderate creepage, whereas flange wear becomes more pronounced in sharp curves because of increased angle of attack, lateral creepage, and concentrated flange contact. Track curvature, operating speed, and suspension characteristics therefore influence the relative development of tread and flange wear [24–25]. This distinction is particularly relevant to HSR systems, where large-radius curves generally reduce the severity of flange contact but do not eliminate creepage-induced tread wear. Because of its clear physical basis, creepage-induced wear provides the foundation for many wheel wear prediction models. Classical physics-based approaches commonly combine Archard-type wear formulations [26] with Hertzian contact theory [27] and Kalker’s creep-force theory [28] to relate wear to contact load, creepage/sliding, and material properties. These models remain widely used in vehicle-track (VT) dynamics and wheel profile evolution simulations because they provide a computationally efficient framework for predicting wear under varying operating and contact conditions.

#### 2.2.2. Flange wear and curving-induced wear

Flange wear is a critical wheel degradation mode associated primarily with curve negotiation, where lateral forces, angle of attack, and contact stresses increase substantially, as shown in Figure 3 [29–30]. In curved tracks, geometric incompatibility between the wheelset and track generates lateral creepage and localized flange rail contact. Compared with tread contact, flange contact is generally more concentrated and involves substantial sliding, promoting adhesive and abrasive wear under high normal pressure. Experimental studies have confirmed that the combination of high contact load and sliding can substantially accelerate flange material loss and promote the transition from wear-dominated damage toward tribo-fatigue mechanisms [31–32].

Flange wear is strongly governed by WR profile geometry. Variations in flange angle, root radius, and rail gauge corner geometry can modify the contact location, pressure distribution, and wheelset guidance characteristics [33–34]. Equivalent conicity also plays a dual role: appropriate conicity can improve wheelset self-steering and reduce flange contact in curves, whereas excessive conicity may increase hunting instability on straight track. Consequently, wheel profile design and reprofiling require a compromise between curving performance, flange wear mitigation, and running stability [35–37].

Vehicle suspension characteristics further influence flange contact through their effects on wheelset steering and yaw behavior. Variations in primary suspension stiffness, yaw resistance, and related maintenance parameters can substantially modify WR forces, wear progression, and vehicle stability [38–39]. These findings indicate that flange wear cannot be attributed solely to track curvature; rather, it results from the interaction among track geometry, WR profiles, suspension characteristics, and operating conditions. Integrated VT dynamic analysis is therefore preferable for predicting flange wear, particularly when transient contact conditions and profile evolution are considered [9].

Although flange wear is generally more pronounced on curved track than on large-radius or straight sections, its cumulative effect can progressively modify wheel geometry and equivalent conicity, thereby altering wheelset guidance and subsequent contact conditions. This establishes a feedback between profile evolution, WR contact, vehicle dynamics, and wear progression, which should be incorporated into long-term wheel wear prediction frameworks.

### 2.2.3. Wear associated with RCF

RCF is a safety-critical degradation mechanism caused by repeated rolling-sliding contact stresses at the WR interface. Cyclic loading can induce localized plastic deformation and initiate surface or subsurface cracks, which may subsequently propagate under repeated contact loading [6]. Although RCF is fundamentally a fatigue process, its development is closely coupled with wear because material removal continuously modifies the surface condition and WR contact geometry [40].

The interaction between wear and RCF is generally competitive and nonlinear. Mild or controlled wear can remove the plastically deformed surface layer containing early-stage fatigue cracks, thereby delaying crack growth and severe defects such as spalling or shelling [41–42]. Conversely, excessive wear can substantially modify the wheel profile and contact geometry, redistribute contact stresses, and create new high-stress regions that may promote RCF initiation [43–45]. At the other extreme, insufficient material removal may allow surface cracks to persist and propagate to greater depths, increasing the risk of severe RCF damage [46]. Experimental and numerical studies further indicate that RCF development depends strongly on normal load, creepage, contact conditions, and pre-existing surface defects [47–49].

For wheel wear prediction, these interactions highlight an important limitation of conventional wear only formulations. Models based primarily on material removal can predict profile evolution but do not explicitly describe crack initiation and propagation. Nevertheless, because the present review focuses on wheel wear prediction rather than dedicated RCF modeling, RCF is considered here primarily as a coupled degradation mechanism that can influence wear progression and wheel profile evolution. Detailed RCF specific approaches and fatigue damage formulations are beyond the scope of this review and warrant dedicated investigation in future work.

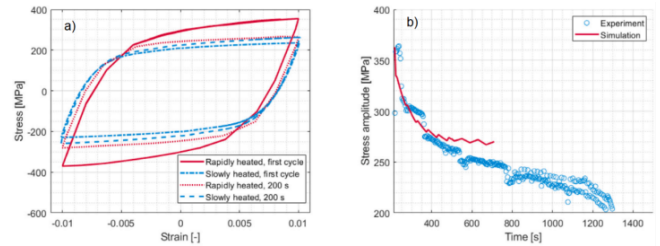


**Figure 4.** (a) Stress-strain curves at 600 °C for rapidly heated and pre-softened specimens. (b) Comparison of stress amplitudes between the rapidly heated experiment and the FEM simulation [50]

### 2.2.4. Thermo-mechanical effects on wheel wear and damage

Thermal effects can influence wheel wear and damage, but their relevance to HSR operation depends strongly on the braking architecture and operating conditions [17]. Modern HSR vehicles predominantly use regenerative braking combined with disc braking, so direct frictional heating of the wheel tread is generally not the dominant thermal loading mechanism during normal operation. Nevertheless, emergency or repeated braking, degraded regenerative braking, and other severe conditions can generate substantial transient thermal loads that modify wheel material properties and affect subsequent wear and RCF evolution.

Experimental and numerical studies have shown that severe frictional heating under tread-braking conditions can cause thermal softening, microstructural changes, residual stresses, and degradation of mechanical properties in railway wheel steels [50–52]. In particular, the experimental and FEM results in [50], shown in Figure 4, demonstrate a pronounced reduction in stress amplitude at 600 °C, indicating temperature-dependent softening of ER7 wheel steel. Such thermal softening can reduce near-surface plastic resistance and increase susceptibility to deformation, wear, and fatigue damage. Wang et al. [53] further reported that prolonged braking-induced temperature rise can promote thermal softening, plastic deformation, and RCF damage. However, these tread-braking conditions should not be interpreted as representative of normal braking operation in modern HSR vehicles.

From a modeling perspective, thermal loading becomes important when temperature-dependent material properties, thermal stresses, and transient heating and cooling significantly affect the mechanical wear process. Thermo-mechanically coupled models have shown that friction-induced temperature rise can accelerate material degradation and modify wear progression, while fully coupled approaches can account for the interaction among temperature evolution, thermal expansion, contact conditions, and wear [54–56].

Therefore, thermal effects in HSR wheel wear prediction should be treated as condition dependent rather than universally dominant. Under normal regenerative and disc-braking operation, their direct contribution to tread wear is expected to be limited, whereas severe braking events may produce significant thermo-mechanical effects. Thermal coupling should consequently be incorporated into wheel wear prediction frameworks when the relevant operating and braking condi-

tions justify its consideration.

#### 2.2.5. Environmentally influenced wear

Environmental conditions modify WR wear primarily by altering adhesion, lubrication, oxidation, and third-body layer behavior. Humidity, temperature, water films, and contaminants can therefore produce highly variable and non-stationary wear regimes that are difficult to represent using constant friction assumptions. Higher humidity or water contamination generally reduces adhesion through boundary or mixed lubrication, whereas dry conditions can increase tangential stresses and promote adhesive and abrasive wear [57–58]. Temperature also affects both tribological behavior and material response. Experimental studies have shown that low temperatures can modify plastic deformation, work hardening, and tribo-film formation, thereby changing the transition between wear- and fatigue-dominated damage mechanisms [59–60].

Third-body layers, including leaves, sand, dust, oxide debris, and brake particles, can either mitigate or accelerate WR wear depending on their composition, stability, and loading conditions. Soft or moisture-rich layers may reduce direct metal-to-metal contact and adhesion, whereas hard particles can promote abrasive wear and surface damage [61–62]. In particular, leaf contamination can cause severe and transient adhesion loss through the formation of water-rich organic-oxide layers at the contact interface, as shown in Figure 5 [63–64]. Conversely, sand and other hard contaminants may increase friction and wear through abrasive mechanisms, while lubricating contaminants can substantially reduce both quantities [65]. These competing effects demonstrate that environmental contamination can simultaneously alter adhesion performance and material degradation.

Environmental conditions also influence the formation and stability of oxide and tribochemical films. Temperature, humidity, and oxygen availability affect oxidation reactions and film regeneration, while repeated rolling and sliding can remove these protective layers and produce transient changes in friction and wear [66–69]. Consequently, environmental effects introduce considerable uncertainty into long-term wheel wear prediction, particularly for HSR systems operating under varying climatic conditions. From a modeling perspective, conventional wear models that assume constant friction and stationary contact conditions may not adequately capture this variability. More robust prediction frameworks should therefore account, where relevant, for environment-dependent friction, third-body layer evolution, and stochastic changes in operating conditions.

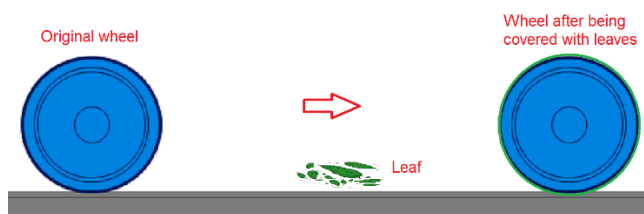


**Figure 5.** Moisture stored in leaves is mechanically released onto the rail surface during WR contact

#### 2.3. Spatial and temporal characteristics of wheel wear evolution

Wheel wear exhibits pronounced spatial heterogeneity, with different regions of the wheel profile experiencing distinct wear rates and mechanisms [70]. Tread and flange wear are governed by different WR contact conditions, including contact geometry, normal load, creepage, and slip. Tread wear is mainly associated with rolling-sliding contact during traction, braking, and curving, whereas flange wear is concentrated in curved-track operation under high lateral forces and creepage. Non-uniform contact conditions consequently lead to asymmetric and nonlinear profile evolution, including the development of hollow wear. Temporally, wheel wear generally evolves through successive stages [71]. After reprofiling, an initial transient stage is characterized by rapid adaptation of the WR contact geometry and relatively high wear rates. A quasi-steady stage may subsequently develop under stable operating conditions, followed by progressive profile deterioration as accumulated mileage changes the contact geometry and stress distribution [72]. Operational and environmental variations can further modify this evolution. These characteristics demonstrate that wheel wear is a history dependent and nonlinear process governed by the evolving wheel profile, accumulated mileage, and changing contact conditions. Therefore, long-term HSR wheel wear prediction requires models capable of updating the wheel profile and associated WR contact.

#### 2.4. Implications for wear prediction modeling

The mechanisms discussed above indicate that wheel wear is a nonlinear, spatially heterogeneous, and history-dependent process. Multiple mechanisms, including adhesive and abrasive wear, plastic deformation, RCF, and thermo-environmental effects, may coexist and vary with wheel profile location, operating condition, and accumulated mileage. Meanwhile, wear continuously modifies the wheel profile and WR contact geometry, which alters contact forces, creepages, and subsequent wear. This bidirectional interaction makes long-term wear evolution difficult to represent using fixed wear laws or simple linear extrapolation. Prediction models should therefore account for the evolving WR contact state and, where relevant, variations in operating, thermal, and environmental conditions. These requirements motivate the use of physics-based, data-driven, and hybrid approaches with different levels of modeling complexity. The following section therefore classifies and evaluates existing wheel wear prediction methods according to their modeling principles, input requirements, predictive capabilities, and applicability to HSR systems.

### 3. Classification of wheel wear prediction methods

No single prediction approach can comprehensively represent wheel wear across different operating conditions and time scales. Existing methods therefore differ in their modeling assumptions, physical representation, and dependence on experimental or operational data. In this review, wheel wear prediction methods are classified into five categories: (i) empirical and semi-empirical models, (ii) physics-based contact and

wear models, (iii) VT-coupled multi-body dynamics (MBD) approaches, (iv) experimental and measurement-driven methods, and (v) data-driven and hybrid frameworks. This classification provides a consistent basis for comparing their theoretical foundations, input requirements, computational cost, predictive capability, and applicability to HSR wheel wear assessment.

### 3.1. Empirical and semi-empirical models

Empirical and semi-empirical models represent one of the most established approaches to wheel wear prediction. They relate material removal to macroscopic variables, typically normal load and accumulated sliding distance, through empirically calibrated parameters [73]. The Archard wear law is a representative formulation, in which wear volume is proportional to normal load and sliding distance. For WR applications, it is commonly implemented in local form to estimate wear depth from contact pressure and local sliding distance, enabling the evolution of the wheel profile to be evaluated.

Ye et al. [74] demonstrated that Archard-type models can provide reliable wheel wear predictions when their parameters are calibrated against measured data. Zeng et al. [75] further showed that data-driven optimization of the wear coefficient can improve prediction accuracy and reduce calibration uncertainty. These studies indicate that the predictive performance of empirical models depends strongly on the quality and representativeness of the calibration data.

The main advantages of this class are simple formulation, low computational cost, and ease of implementation, making it suitable for parametric analysis and long-term simulations. Its main limitation is the limited physical transferability of calibrated wear coefficients across different WR material pairs, lubrication conditions, environmental states, and operating regimes. For HSR, this limitation becomes more pronounced because contact conditions and wheel profiles evolve continuously with operating mileage. Thus, empirical and semi-empirical models are useful for trend prediction and computationally efficient assessment, but their reliability for long-term prediction under variable operating conditions depends strongly on appropriate calibration and updating of model parameters.

### 3.2. Physics-based contact and wear models

Physics-based contact and wear models describe WR interaction using contact mechanics, local kinematics, and material response rather than relying solely on empirical correlations [76]. Wear is typically evaluated from local contact pressure, creepage or slip, and energy dissipation, with Hertzian, semi-Hertzian, non-Hertzian, or elastic-plastic contact formulations coupled with appropriate wear laws [77]. Recent developments have extended classical Hertzian formulations toward more realistic non-Hertzian approaches to improve the representation of complex WR geometries and dynamic contact conditions, as illustrated in Figure 6.

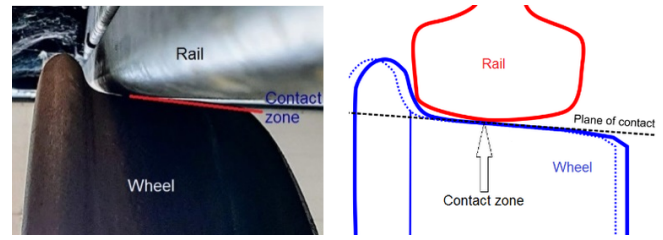


Figure 6. The WR contact

Several studies have demonstrated the potential of advanced contact formulations to improve the accuracy efficiency trade-off in wheel wear prediction. Experimental measurements combined with FEM analysis have confirmed the applicability of Hertzian-type contact models while highlighting the influence of contact geometry and loading conditions [78]. Non-Hertzian formulations based on the CONTACT framework can represent unsteady tangential contact with lower computational cost through appropriate linearization strategies [79]. Comparative studies of Hertzian, semi-Hertzian, and non-Hertzian formulations further showed that the choice of contact model affects both vehicle dynamics and wear prediction, with semi-Hertzian and simplified non-Hertzian approaches providing favorable compromises between accuracy and computational efficiency for large-scale simulations [80–82].

An important advantage of physics-based models is their ability to provide spatially resolved wear distributions and to relate profile evolution to local WR contact conditions. They can therefore distinguish tread and flange wear, and capture localized changes in wear depth and contact position [83–85]. This capability is particularly relevant to HSR, where small variations in wheel geometry can modify contact conditions, subsequently affect wheel dynamics and wear evolution.

Predictive accuracy remains sensitive to the representation of WR geometry, material behavior, and surface conditions. Models assuming smooth surfaces and purely elastic or homogeneous materials may not adequately represent the effects of roughness, plastic deformation, temperature-dependent properties, or surface topography. Experimental and numerical studies have demonstrated that incorporating surface roughness, elastic-plastic behavior, thermal effects can substantially modify predicted contact stresses and material response [86–88]. Environmental effects such as lubrication, oxidation, and third-body layers are also commonly simplified or treated separately. Another limitation is the incomplete coupling between local contact/wear calculations and vehicle dynamics. When prescribed WR forces or contact conditions are used, the feedback from wear-induced profile evolution to WR contact and vehicle response may not be fully captured [89]. Thus, physics-based models provide high physical interpretability, localized wear prediction, but their computational cost and incomplete dynamic coupling can limit their standalone application to long-term HSR simulations. Coupling with MBD, thermal, or data-driven models can improve their applicability to realistic operating conditions.

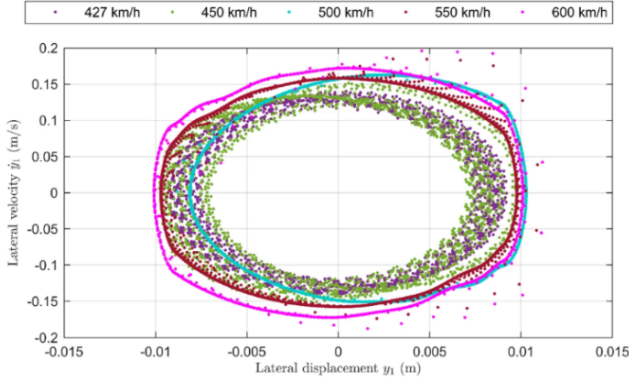


**Figure 7.** Phase portraits of the railway vehicle bogie [94]

### 3.3. VT-coupled MBD approaches

VT-coupled MBD approaches integrate vehicle dynamics, WR contact mechanics, track irregularities, and wheel wear within a unified simulation framework. Unlike decoupled approaches, these models capture the reciprocal interaction between wheel-profile evolution, contact forces, suspension dynamics, and track excitation, thereby providing a more physically consistent basis for long-term wear prediction [7]. MBD-based approaches are particularly relevant because high operating speeds amplify the effects of vehicle inertia, suspension characteristics, track irregularities, and hunting instability. These factors produce transient variations in WR contact forces, creepage, contact locations, which directly affect the magnitude and spatial distribution of wheel wear [90–95]. For example, nonlinear dynamic simulations have shown that hunting stability is strongly influenced by equivalent conicity, suspension parameters, and operating speed; the resulting lateral and yaw oscillations can modify contact conditions and contribute to localized wear, as illustrated in Figure 7 [94].

A major advantage of VT-coupled MBD approaches is their ability to capture the bidirectional feedback between wheel wear and vehicle dynamics. As the wheel profile evolves, contact geometry and force distribution change, which subsequently modify the vehicle response and further influence wear progression [96]. Recent studies have confirmed that time-dependent wheel profile evolution can affect curving performance, straight-line running, ride comfort, stability, and dynamic WR interaction [97–99]. This capability makes MBD particularly suitable for HSR applications where long-term wear and dynamic performance are strongly coupled. However, MBD-based wear prediction requires detailed vehicle, track, contact, and operational data and is computationally demanding, especially for long-distance simulations involving repeated wheel profile updates. Therefore, its practical application to large-scale or real-time prediction generally requires efficient contact formulations, model reduction, surrogate modeling, or integration with data-driven methods.

### 3.4. Experimental and measurement-driven prediction methods

Experimental and measurement-driven approaches use field measurements and laboratory tests to characterize wheel wear and provide data for model calibration and validation. These approaches are directly linked to observed wheel degrada-

tion and operating conditions, making them essential for assessing the practical reliability of wear predictions. Periodic wheel profile measurements using tread gauges, laser scanners, profilometers, and image-based systems provide direct information on profile evolution, including tread wear and flange geometry [100–102]. Time-series measurements can be used to estimate wear rates, calibrate empirical parameters, and validate numerical predictions. Non-contact techniques have increasingly improved measurement efficiency and accuracy, while also enabling large-scale monitoring. In parallel, onboard monitoring systems incorporating accelerometers, wheel-dimension sensors, optical devices, impact detectors enable continuous assessment of wheel condition and abnormal degradation [103–105]. These systems provide higher temporal resolution than periodic inspections and offer opportunities for condition-based maintenance, data-driven wear prediction.

Laboratory experiments, particularly twin-disc full-scale WR tests, provide controlled conditions for investigating wear mechanisms quantifying the effects of normal load, slip ratio, temperature, and other operating parameters. Such experiments can isolate specific wear regimes and provide wear coefficients or experimental relationships for numerical models [106–108]. For example, twin-disc tests have been used to reproduce rolling, sliding, and RCF conditions while systematically varying contact parameters, as illustrated in Figure 8 [106]. Field measurements are often costly and provide sparse observations, while onboard systems may be affected by sensor noise, calibration requirements, and maintenance constraints. Laboratory tests cannot fully reproduce the coupled dynamic, environmental, and operational conditions of HSR service. Therefore, experimental data are most effectively used in combination with physics-based or data-driven models, rather than as a standalone solution for long-term wheel wear prediction.

### 3.5. Data-driven and hybrid prediction frameworks

Recent advances in sensing, data acquisition, and machine learning (ML) have enabled data-driven approaches for wheel wear prediction. These methods learn nonlinear relationships between operational conditions, vehicle responses, and wear indicators without explicitly resolving the underlying wear mechanisms. Their main advantages are computational efficiency, the ability to exploit large operational datasets, although prediction performance remains strongly dependent on data quality, coverage, and representativeness. Hybrid frameworks combine data-driven learning with physics-based models to overcome the limitations of purely data-driven approaches. Sresakoolchai et al. [109], for example, integrated supervised and reinforcement learning for wheel wear management and maintenance optimization. Other studies have combined VT physical models with neural networks to predict WR force dynamics, demonstrating good agreement with measured data [110]. Similarly, model- and data-driven approaches have been combined to improve the identification of wear coefficients and reduce prediction uncertainty [111]. A further development is the incorporation of physical constraints into ML models. Physics-informed and

mechanism-data dual-driven frameworks can use physical laws, simulation results, or known wear trends to constrain model predictions, which is particularly beneficial when field measurements are sparse or noisy [112–113]. Such approaches can improve generalization while reducing the risk of physically implausible predictions. Recent studies have also extended these concepts toward remaining useful life (RUL), wheel RCF life prediction, and explainable predictive maintenance using operational and onboard monitoring data [114–116].

Data-driven and hybrid methods remain limited by the availability, quality of labelled wear data, model transferability across vehicles, operating environments, and the interpretability of complex learning architectures. Their most promising application to HSR wheel wear prediction therefore lies in combining physics-based knowledge, MBD simulations, field measurements to improve generalization while retaining sufficient physical consistency.

#### 4. Comparative analysis of wheel wear prediction methods

This section critically compares the five categories of wheel wear prediction methods in terms of physical fidelity, data requirements, computational efficiency, predictive capability, and suitability for HSR applications.

##### 4.1. Systematic comparison of prediction methods

Table 1 summarizes the main characteristics of the five categories of wheel wear prediction methods, including required inputs, typical outputs, spatial and temporal scales, as well as their principal advantages and limitations.

This comparison highlights that no single approach simultaneously achieves high accuracy, computational efficiency, and broad applicability, thereby reinforcing the need for method selection to be guided by specific application objectives.

##### 4.2. Suitability for HSR applications

HSR wheel wear prediction requires methods capable of accounting for speed-dependent vehicle dynamics, evolving WR contact conditions, safety constraints, and long service intervals. The suitability of the five categories can therefore be summarized as follows.

Empirical and semi-empirical models offer high computational efficiency and are suitable for fleet-level trend assessment, rapid screening, and preliminary maintenance planning. Their dependence on calibrated wear coefficients limits their transferability when dynamic, environmental, and profile-evolution effects vary substantially.

Physics-based models provide greater physical interpretability and spatially resolved prediction of local wear mechanisms. They are particularly useful for investigating the effects of contact geometry, creepage, material properties, and wear mechanisms. Their computational cost and limited system-level coupling constrain their standalone application to long-term HSR prediction.

VT-coupled MBD approaches provide the most comprehensive representation of the interaction between wheel wear

and vehicle dynamics. They can capture speed-dependent contact-force fluctuations, hunting instability, suspension effects, and wear-induced changes in contact geometry. Their main limitation is computational cost, particularly for long-distance simulations requiring repeated profile updates.

Experimental and measurement-driven approaches provide essential field and laboratory evidence for calibration and validation. Their main limitations are measurement cost, sparse observations, sensor uncertainty, and incomplete representation of the full range of operating conditions. They are therefore more effective as a data source for model development than as a standalone long-term prediction framework.

Data-driven and hybrid approaches offer high computational efficiency and can exploit operational and onboard monitoring data to identify complex nonlinear relationships. Their main limitations are data availability, model generalization, and physical interpretability. Hybrid approaches that incorporate physics-based constraints or MBD-generated data are therefore particularly promising for improving robustness under sparse or variable operating conditions.

Table 2 summarizes representative studies according to their prediction methodology, application context, and principal limitations, providing additional evidence for this comparative assessment.

#### 5. Open issues and future research directions

##### 5.1. Open issues

Despite substantial methodological progress, several challenges continue to limit the accuracy, transferability, and practical deployment of wheel wear prediction for HSR systems:

- (1) Most existing models focus on individual wear mechanisms or use simplified coupling assumptions. The interactions among rolling-sliding wear, RCF, thermo-mechanical effects, and dynamic loading remain insufficiently represented, limiting the physical completeness of long-term predictions.
- (2) Multi-scale integration. The connection between local WR contact phenomena, such as stress, creepage, and micro-slip, and system-level VT dynamics remains insufficiently established. This limits the reliable prediction of cumulative wear and its feedback on vehicle performance.
- (3) VT-coupled MBD models provide high physical fidelity, their computational cost remains a major barrier to long-distance simulation, fleet-scale assessment, and optimization-based maintenance.
- (4) ML-based approaches remain sensitive to data quality, operating-condition coverage, and model transferability. Ensuring physically consistent predictions under unseen conditions remains particularly important for HSR.
- (5) The limited availability of standardized, long-term experimental datasets under sustained high-speed service conditions continues to impede rigorous model validation, benchmarking, and the development of reliable hybrid prediction frameworks.

**Table 1.** Comparative overview of wheel wear prediction methods

| Method category                      | Typical inputs                                                          | Typical outputs                                        | Scale        | Advantages                                                                                        | Limitations                                                                                       |
|--------------------------------------|-------------------------------------------------------------------------|--------------------------------------------------------|--------------|---------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------|
| Empirical/<br>semi-empirical         | Axle load, speed,<br>curvature, wear<br>coefficients                    | Average wear rate,<br>mileage-based wear               | Macro        | Simple, low computational<br>cost, easy to implement                                              | Strong dependence on<br>calibration; limited<br>generalization; weak physical<br>interpretability |
| Physics-based contact<br>& wear      | Contact geometry,<br>material properties,<br>creepage, friction         | Local wear depth,<br>tread/flange wear<br>distribution | Meso-micro   | Physically interpretable;<br>captures local wear behavior                                         | Sensitive to assumptions;<br>limited dynamic coupling; high<br>modeling complexity                |
| Coupled MBD-based                    | Vehicle parameters,<br>suspension, track<br>geometry, contact<br>models | Wear evolution,<br>profile change,<br>dynamic response | System-level | Captures interaction between<br>wear and vehicle dynamics;<br>suitable for system<br>optimization | Computationally intensive;<br>large input data requirements                                       |
| Experimental /<br>measurement-driven | Wheel profiles,<br>onboard sensors, test<br>rig data                    | Observed wear<br>evolution, empirical<br>trends        | Macro-meso   | High fidelity to real behavior;<br>essential for validation                                       | Costly; limited prediction<br>horizon; poor extrapolation                                         |
| Data-driven/hybrid                   | Operational data,<br>sensor signals,<br>historical wear data            | Wear prediction, RUL                                   | Macro-system | Handles complex<br>nonlinearities; scalable                                                       | Data dependency; limited<br>interpretability; generalization<br>challenges                        |

**Table 2.** Summary of representative studies on wheel wear prediction methods

| Method category                | Railway context                      | Wear focus                   | Key contribution                                                         | Main limitation                              | Ref.  |
|--------------------------------|--------------------------------------|------------------------------|--------------------------------------------------------------------------|----------------------------------------------|-------|
| Semi-empirical                 | General railway                      | Wear severity                | Semi-analytical method for predicting WR<br>wear severity                | Requires calibration;<br>simplified dynamics | [73]  |
| Semi-empirical                 | Railway                              | Wheel wear rate              | Calibration framework for existing wear<br>models                        | System-specific<br>parameters                | [74]  |
| Empirical + data-driven        | Railway                              | Wheel wear                   | Data-driven optimization of Archard<br>parameters                        | Limited physical<br>interpretability         | [75]  |
| Physics-based (FEM)            | WR contact                           | Thermo-mechanical<br>wear    | High-fidelity thermomechanical FEM model<br>with experimental validation | High computational cost                      | [76]  |
| Physics-based                  | WR contact                           | Energy dissipation &<br>wear | Wear modeling based on power dissipation                                 | Limited system-level<br>coupling             | [77]  |
| Physics-based                  | Curved track                         | Flange wear                  | Conformal and lubricated contact effects on<br>flange wear               | Case-specific geometry                       | [83]  |
| Physics-based + MBD            | HSR                                  | Tread wear                   | Comparison of contact models under varying<br>friction                   | Dependent on contact<br>assumptions          | [89]  |
| MBD                            | Railway                              | Profile wear                 | Comprehensive overview of numerical wear<br>models                       | Limited focus on<br>high-speed wheels        | [7]   |
| MBD                            | Railway                              | Wheel wear                   | Benchmarking of modeling choices in MBD<br>wear prediction               | Computational demand                         | [96]  |
| MBD                            | HSR                                  | Profile evolution            | Effect of time-varying wear on vehicle<br>dynamics                       | Requires long-term<br>simulation             | [97]  |
| MBD + surrogate                | High-speed Electric<br>Multiple Unit | Wheel wear &<br>dynamics     | Surrogate-based optimization for wear<br>reduction                       | Surrogate accuracy<br>dependence             | [98]  |
| Measurement-driven             | Railway                              | Wheel profile                | Use of laser-based measurements in<br>simulations                        | Measurement uncertainty                      | [100] |
| Data-driven                    | HSR                                  | Out-of-round wheels          | Deep learning for onboard wheel condition<br>monitoring                  | Limited wear mechanism<br>insight            | [103] |
| Data-driven                    | Railway                              | Flange wear                  | ML-based onboard flange wear measurement                                 | Sensor/data dependency                       | [105] |
| Physics-based +<br>data-driven | Railway                              | Wheel wear                   | Physics-guided data-driven wear modeling                                 | Model complexity                             | [85]  |
| Hybrid ML                      | Railway                              | Wheel wear<br>management     | Hybrid supervised-reinforcement learning                                 | Limited field validation                     | [109] |
| Data-driven                    | Railway                              | Hollow wear                  | RUL estimation using vibration-based tread<br>depth                      | Route-specific<br>generalization             | [116] |

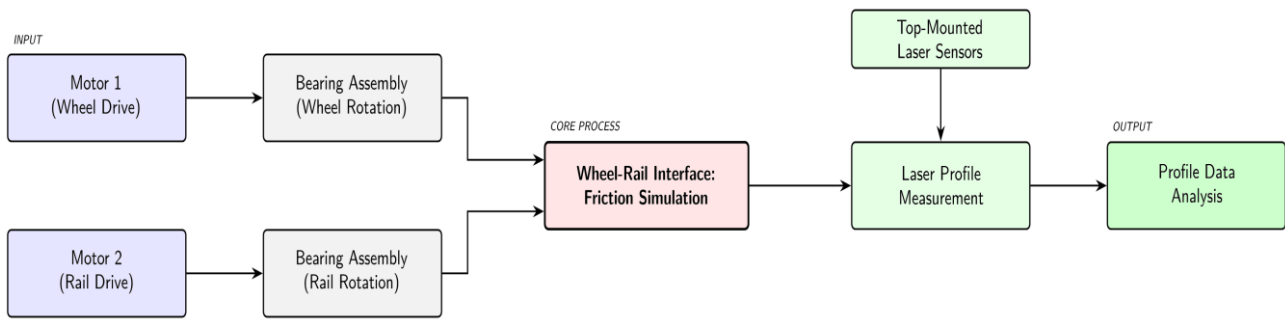


Figure 8. Schematic layout of the WR friction test system

## 5.2. Future research directions

The principal future research directions can be outlined as follows:

- (1) Wear, RCF, and relevant thermo-mechanical effects should be incorporated within physically consistent frameworks where their interactions are represented according to the operating conditions.
- (2) Local contact and material models should be coupled with reduced-order VT dynamics to balance physical fidelity and computational efficiency.
- (3) Future research should develop reduced-order and surrogate models to enable real-time HSR wheel wear prediction and support digital twins and predictive maintenance.
- (4) Integrating physical constraints and domain knowledge into ML frameworks can improve the robustness, generalizability, and reliability of data-driven wheel wear prediction for HSR.
- (5) Integrating wheel profile measurements with onboard and wayside monitoring data can support digital-twin-based prediction, enabling real-time wheel condition assessment, predictive maintenance, and operational optimization.
- (6) Standardized, high-quality HSR datasets and benchmarking procedures are essential for objective comparison, reproducibility, and rigorous validation of wheel wear prediction methods.

Overall, future HSR wheel wear prediction is expected to move toward integrated and hybrid frameworks that combine physical modeling, vehicle dynamics, sensing, and data analytics while maintaining computational feasibility and physical interpretability.

## 6. Conclusions

A comprehensive and systematic review of prediction methods for wheel wear in HSR systems has been presented in this paper, with specific emphasis placed on the wheel as a critical and distinct component of the WR interface. Through the synthesis of research encompassing empirical, physics-based, numerical, experimental, and data-driven approaches, a structured overview of the current state of the art has been provided, and the strengths and limitations of existing methodologies have been clarified. Based on the comprehensive literature review conducted in this study, the principal research findings and methodological advancements achieved to date

can be summarized as follows:

- (1) The complex and multi-physical nature of wheel wear under high-speed operating conditions has been highlighted, in which rolling and sliding wear, RCF-related material removal, thermal effects, material behavior, and VT dynamics interact across multiple spatial and temporal scales. This inherent complexity fundamentally constrains the applicability of prediction approaches based on a single modeling paradigm.
- (2) A classification framework for wheel wear prediction methods has been established, enabling systematic comparison in terms of modeling philosophy, physical fidelity, computational efficiency, and data requirements. The comparative analysis indicates that while empirical and physics-based models provide modeling simplicity and physical insight, respectively, coupled VT MBD approaches offer the most comprehensive representation of wheel wear evolution under high-speed conditions, albeit at the expense of high computational cost. Data-driven and hybrid methods are identified as promising alternatives; however, their applicability remains limited by challenges related to data availability, generalization capability, and physical interpretability.
- (3) Several key research gaps have been identified, including the limited integration of multiple wear and damage mechanisms, the absence of consistent multi-scale modeling strategies, the lack of real-time capable prediction models, and the scarcity of standardized datasets for validation and benchmarking, particularly under long-term high-speed service conditions.

Based on these findings, future research directions have been outlined, emphasizing the development of hybrid and physics-informed prediction frameworks, reduced-order modeling techniques, advanced sensing and digital twin integration, and standardized benchmarking practices. These directions are expected to play a pivotal role in advancing wheel wear prediction toward reliable, scalable, and operationally relevant tools for predictive maintenance and system optimization in HSR networks.

Overall, this review is intended to serve as a reference framework for both researchers and practitioners, supporting informed method selection, guiding future methodological development, and facilitating the transition toward condition-based and predictive maintenance strategies for HSR wheels.

### Author contributions

Hue Phuoc Lu: Methodology, Data compilation, Data analysis, Formal analysis, Feedback on peer review, Writing – original manuscript. Dong Doan Van: Data management, Methodology, Data compilation, Data analysis, Formal analysis, Feedback on peer review, Writing – original manuscript.

### Declaration of competing interest

The authors declare the absence of any potential conflicts of interest from this study and affirm that the paper has not been previously published.

### Data availability

No new data were generated or analyzed in this review. All information is based on the published literature cited in this article.

### Acknowledgements

This work was supported by Ho Chi Minh City University of Transport.

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