

Railway Wheel Damage: Mechanisms, Monitoring, and Prediction

Tengchi Sun¹, Ruichen Wang^{1*}, Haotian Lyu¹, Jiale Zhang¹, Zifei He¹

¹School of Mechanical Engineering, Shijiazhuang Tiedao University, Shijiazhuang 050043, China

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*Corresponding author: ruichen.wang@stdu.edu.cn

Abstract: Wheel damage remains a major constraint on railway safety, dynamic performance, asset life, and maintenance efficiency. Despite extensive studies of individual damage modes, understanding remains fragmented across mechanisms, monitoring, prediction, and maintenance application. This review provides an integrated synthesis of damage formation, measurable evidence, predictive modelling, and maintenance relevance. It examines four major damage modes, namely polygonal wear, wheel flats, rolling contact fatigue, and hollow wear, and clarifies the mechanisms and influencing factors governing their initiation, coupling, and evolution. Bench testing and in-service monitoring are assessed as complementary evidence sources for mechanism validation, parameter calibration, diagnosis, prediction, and maintenance assessment. Prediction studies fall into three paradigms: physics-based, data-driven, and hybrid approaches. Physics-based approaches retain mechanistic value for long-term profile evolution but depend on accurate contact representation and impose high computational cost. Data-driven approaches support efficient diagnosis and short-term prediction but remain constrained by data quality, label scarcity, drift, and cross-domain transfer. Hybrid approaches combine physical structure with data adaptability but still require field validation and maintenance-oriented evaluation. The main barrier is weak integration among mechanism interpretation, sensing evidence, predictive capability, and maintenance criteria. Future progress depends on benchmark datasets, transferable monitoring and prediction frameworks, uncertainty-aware evaluation, and stronger links between model outputs and maintenance decision-making.

Keywords: railway wheel damage; wheel wear; rolling contact fatigue; polygonal wear; condition monitoring; predictive modelling

1. Introduction and Scope of the Review

As railway systems move towards higher speeds, heavier axle loads, and more intelligent operation, wheel condition has become central to safety, ride quality, component life, and maintenance efficiency. Damage on the wheel tread alters contact geometry, changes force transmission at the wheel-rail interface, and can accelerate deterioration in both vehicle and track systems [1]. Railway wheel damage has therefore become a major topic in wheel-rail dynamics, tribology, condition monitoring, and maintenance research. Existing studies have examined wheel damage from several perspectives, including damage mechanisms, material matching, operating conditions, bench testing, in-service monitoring, and prediction. The literature, however, remains dispersed across damage modes and disciplinary viewpoints, and the terminology is not always applied with sufficient precision. In particular, the relation between the broad concept of wheel damage and the narrower concept of wheel wear is often left unclear. That lack of clarity weakens the structure of a review and complicates the interpretation of modelling studies, because many prediction frameworks focus on wear evolution rather than the full range of wheel damage.

In the present review, railway wheel damage is used as an umbrella term covering wear-related profile deterioration, wheel out-of-roundness, localised tread defects, and rolling contact fatigue developed in service, whereas wheel wear refers more specifically to progressive material removal and profile evolution under rolling-sliding contact. On

that basis, the paper reviews the principal damage modes and the mechanisms associated with their formation, examines the main factors governing damage evolution, evaluates the evidence provided by bench testing and in-service monitoring, and compares physics-based, data-driven, and hybrid prediction approaches in relation to engineering application. The central argument is that progress in wheel damage research now depends less on isolated advances in individual areas than on stronger integration among mechanism interpretation, sensing evidence, prediction, and maintenance decision-making. Section 2 describes the review methodology, including the search strategy, screening procedure, appraisal criteria, and literature classification used to support the subsequent synthesis. Section 3 outlines the major damage modes and associated mechanisms. Section 4 examines the principal factors governing damage evolution. Section 5 evaluates diagnostic evidence from bench testing and in-service monitoring. Section 6 reviews current prediction approaches and compares strengths, limitations, and maintenance relevance. Section 7 summarises the main conclusions, identifies the remaining gaps, and outlines priorities for future research. Throughout the review, the discussion is framed by a full-chain perspective linking damage formation, sensing, prediction, and maintenance.

Compared with previous reviews that focus mainly on wheel wear, rolling contact fatigue, polygonal wear, or condition monitoring as separate topics, this review emphasises a full-chain perspective. Its contribution is not only to summarise individual damage mechanisms or diagnostic methods, but also to connect damage formation, sensitive monitoring signals, prediction model

selection, uncertainty-aware evaluation, and maintenance decision-making within one integrated framework. This mechanism-to-maintenance structure is intended to clarify how physical understanding, sensing evidence, and predictive models can jointly support condition-based wheel damage management.

2. Review Methodology

This review adopts a structured narrative-integrative approach rather than a quantitative meta-analysis. Its purpose is to synthesise railway wheel damage research across four connected domains: damage mechanisms, influencing factors, monitoring

evidence, and prediction methods. Publications from January 2015 to December 2025 were searched in Web of Science and CNKI using combinations of terms related to railway wheels, wheelsets, wheel wear, polygonal wear, wheel flats, rolling contact fatigue, monitoring, prediction, data-driven methods, and machine learning. The PRISMA-style process in Fig. 1 summarises the literature identification and eligibility screening procedure. The search identified 311 database records, and backward reference tracking added 24 foundational studies. After duplicate removal, title-and-abstract screening, full-text assessment, and reference tracking, 170 publications were retained for detailed synthesis.

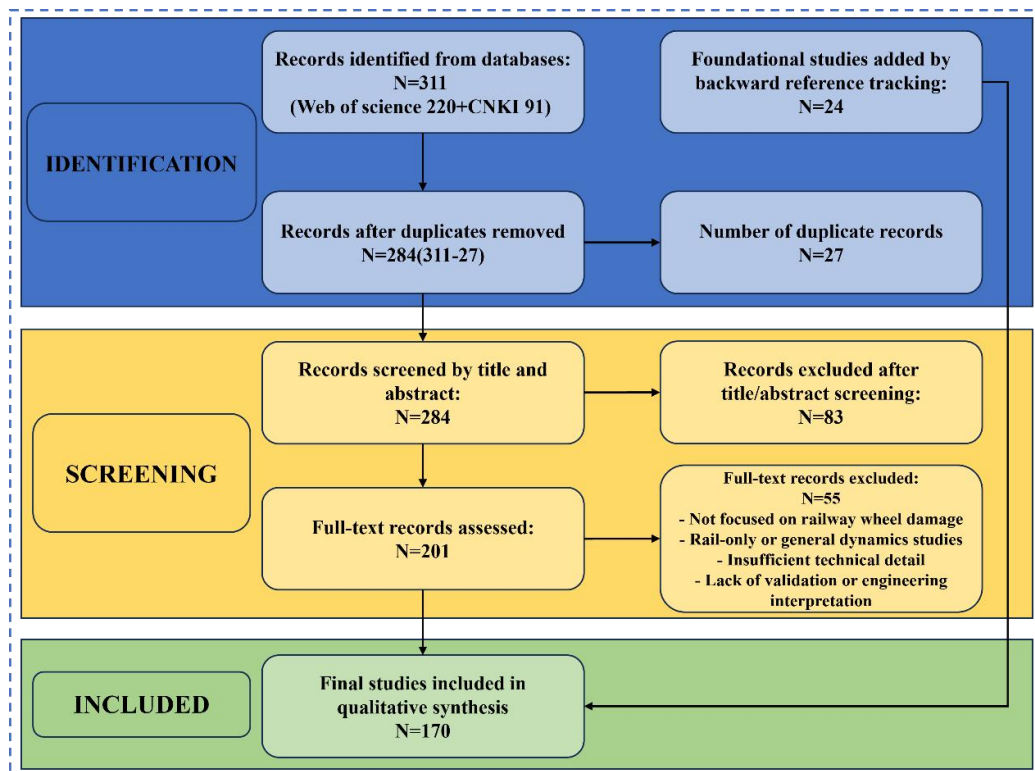


Fig. 1. PRISMA-style literature selection process.

Studies were included when they addressed damage formation mechanisms, influencing factors, bench testing, in-service monitoring, prediction models, or maintenance-related interpretation. Studies were excluded when they focused only on rail defects without clear wheel-damage relevance, general

vehicle dynamics without damage analysis, insufficiently described proprietary systems, or methods lacking validation or engineering interpretation. Fig. 1 therefore documents the screening process, whereas the quality and engineering relevance of the retained studies were appraised after inclusion using six

engineering-oriented criteria: damage-definition clarity, evidence source, validation strategy, reported quantitative indicators, engineering interpretability, and maintenance relevance. These criteria were used as a qualitative appraisal benchmark to distinguish studies with direct, validated, quantitative, and maintenance-relevant evidence from studies used mainly for mechanistic or exploratory interpretation.

During full-text extraction, the six criteria were applied consistently to all 170 retained publications. The extent and directness with which each study addressed these criteria were assessed in relation to its objectives, methods, validation, quantitative evidence, engineering interpretation, and maintenance relevance. These assessments informed each study’s thematic role and contribution to the full-chain synthesis. To make the appraisal traceable within the review, the evidence strength of representative studies was summarised as High, Medium, or Low in Appendix Table A1. High denotes direct and well-supported evidence, with appropriate validation and clear engineering relevance; Medium denotes a meaningful but more

focused contribution, or evidence validated under specific conditions; and Low denotes preliminary or exploratory evidence used mainly to support mechanism interpretation, method development, or the identification of research gaps. These annotations describe the role and strength of each study’s contribution within this review and are not intended as formal quality scores, risk-of-bias assessments, or meta-analytic estimates.

The retained publications were classified according to their role in the full-chain review framework. Four principal damage modes were identified as dominant themes: polygonal wear, wheel flats, rolling contact fatigue, and hollow wear. Monitoring studies were grouped into force- and vibration-based, acoustic-based, and optical-based methods, while prediction studies were categorised as physics-based, data-driven, or hybrid approaches. Table 1 summarises the thematic distribution of the reviewed literature and links the methodology to the technical structure of the review. Counts are approximate and non-exclusive because one publication may contribute to more than one thematic category.

Table 1. Distribution of reviewed publications across thematic categories

Thematic category	Sub- categories	Approximate number of references	Role in full-chain integration
Damage mechanisms	Polygonal wear, wheel flats, rolling contact fatigue, hollow wear	~47	Explains damage initiation laws, identifies sensitive response features, and determines priority monitoring signal types as well as the physical mechanisms that must be embedded in prediction models.
	Hardness matching, material properties, operational conditions, environmental conditions	~23	Defines service conditions that affect damage evolution and model parameters, provides quantitative thresholds and trade- offs for calibrating model coefficients, and

			guides context- specific maintenance priorities.
Monitoring evidence	Bench testing; force- and vibration-based methods; acoustic-based methods; optical-based methods	~40	Provides experimental data for mechanism validation and model calibration; real- time monitoring signals support diagnosis and trigger conditions, forming a closed loop for model input and feedback.
Prediction approaches	Physics-based approaches; data-driven approaches; hybrid approaches	~60	Physics- based approaches interpret long- term evolution, data- driven approaches enable efficient diagnosis, and hybrid approaches combine both to support damage- evolution prediction and maintenance- oriented decision- making.

3. Damage Modes and

Formation Mechanisms

Based on the definition established in the Introduction, this section reviews the main damage modes and their formation mechanisms.

3.1 Wheel Out-of-Roundness: Polygonal Wear

Wheel polygonal wear refers to wavy, non-uniform wear distributed along the wheel circumference and represents a typical form of full-circumferential non-circular wear [2]. According to circumferential regularity, polygonal wear may be classified as periodic or non-periodic [3]. Fig. 2(a) shows a representative field case. In engineering practice, Fourier analysis is widely used to identify polygonal order and wavelength.

The number of periodic undulations around the wheel circumference is commonly described as the polygonal order. In engineering analysis, Fourier methods are used to identify the dominant orders and the associated wavelengths. As indicated by Eq. (1), polygonal order, wheel radius, and rolling speed together determine the characteristic excitation frequency generated by the damaged wheel. Polygonal wear can therefore introduce strong periodic excitation, accelerate degradation in both wheel and track components, and increase operational risk. Zhai et al. [4] provided a systematic review of non-uniform wheel-rail wear in China's high-speed railway system, which further illustrates the engineering significance of the problem.

$$f_n = \frac{vn}{2\pi r} \quad (1)$$

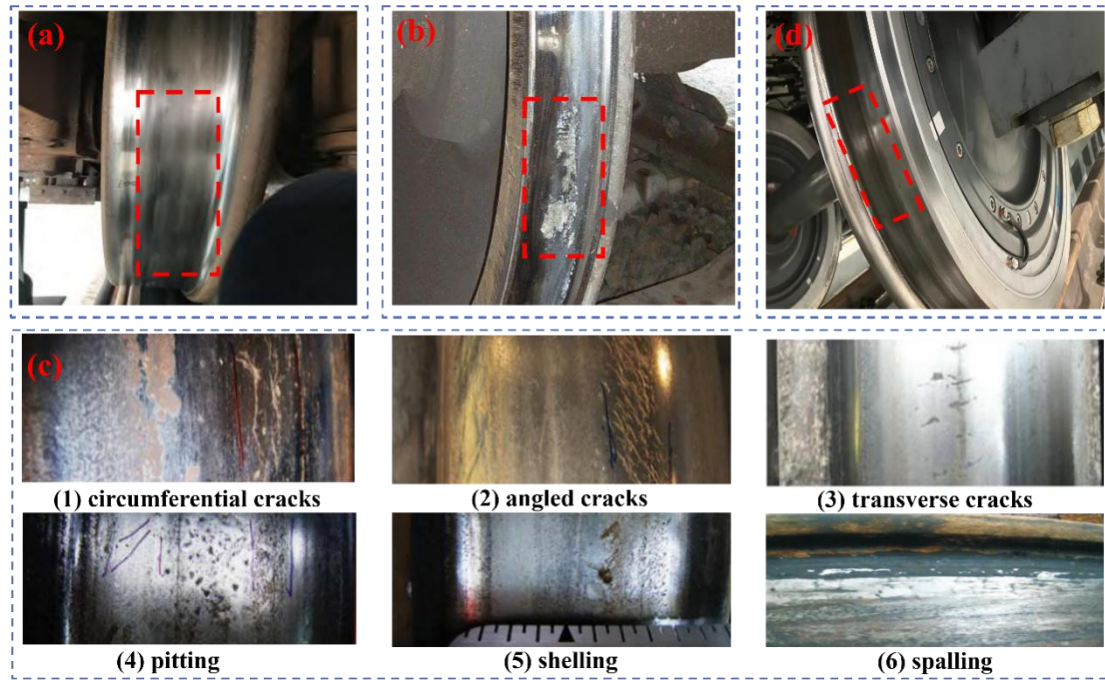


Fig. 2. Principal railway wheel damage modes: (a) polygonal wear; (b) wheel flat; (c) common forms of rolling contact fatigue on wheel treads; (d) hollow wear.

A large body of work has examined the initiation and growth of wheel polygonal wear, yet no single mechanism explains all reported cases. Early studies focused mainly on low-order forms, whereas later work addressed higher-order patterns found in modern metro, locomotive, and high-speed applications. On the basis of the current literature, the main interpretations fall into three mechanism families: resonance-driven excitation, friction-induced self-excited vibration, and initial-defect-triggered feedback.

1) Resonance-driven excitation

Nielsen and Johansson [5] reported frequent low-order polygonal wear on disc-braked ICE wheels, with amplitudes of about 1 mm. Morys [6] coupled multi-body dynamics with wear modelling to analyse polygonal wear evolution in ICE service and identified a strong contribution from wheelset bending modes. Jin et al. [7] showed that wheelset bending resonance can generate large creep-force fluctuations in the contact zone, which

then promote non-uniform plastic deformation and wear accumulation on the tread. Tao et al. [8] indicated that rail corrugation in small-radius curves can excite wheelset bending resonance. Wu et al. [9] also identified wheelset bending resonance as a key driver of polygonal wear and showed that growth becomes faster when wheel circumference approaches an integer multiple of the system resonance wavelength; speed adjustment can interrupt that coupling and suppress further growth. Li [10] further showed that wheelset bending frequency corresponds to characteristic wavelengths generated at specific operating speeds, consistent with the observed polygonal orders.

Fröhling et al. [11] identified torsional vibration of the wheel–axle assembly as a primary excitation source in locomotive wheel polygonal wear and established a quantitative relation among torsional frequency, vehicle speed, and polygonal order. Peng et al. [12] developed a rigid–

flexible coupled locomotive dynamics model with a flexible wheelset and showed that stick-slip vibration, under conditions such as small-radius curves or high traction torque, can excite wheelset torsional modes and initiate polygonal wear. Ma et al. [13] linked polygonal wear initiation to third-order track bending resonance in the bogie region and further indicated that resonance between adjacent bogies can accelerate wear growth. Cai et al. [14] reached a similar conclusion and showed that local rail bending modes contribute to polygonal wear evolution. P2 resonance may be interpreted as a coupled vibration mode involving the vehicle mass below the primary suspension and the track structure. Using coupled dynamics models of subway vehicles and floating slab track, Cai et al. [15] and Yang et al. [16] analysed the

combined effects of wheel-rail P2 resonance and wheelset flexible modes on polygonal wear formation. Wu et al. [17], through tracking tests, showed that when local bogie-frame resonance coincides with the passing frequency of 23rd-order polygonal wear, periodic creep-force fluctuation causes non-uniform wear. Growth becomes more pronounced when the wear wavelength approaches an integer multiple of wheel circumference, whereas speed adjustment can break the resonance condition.

Fig. 3 summarises the three main resonance types discussed in the literature, namely local bogie-frame resonance, wheelset bending resonance, and track P2 resonance, together with the proposed role of each resonance type in polygonal wear formation.

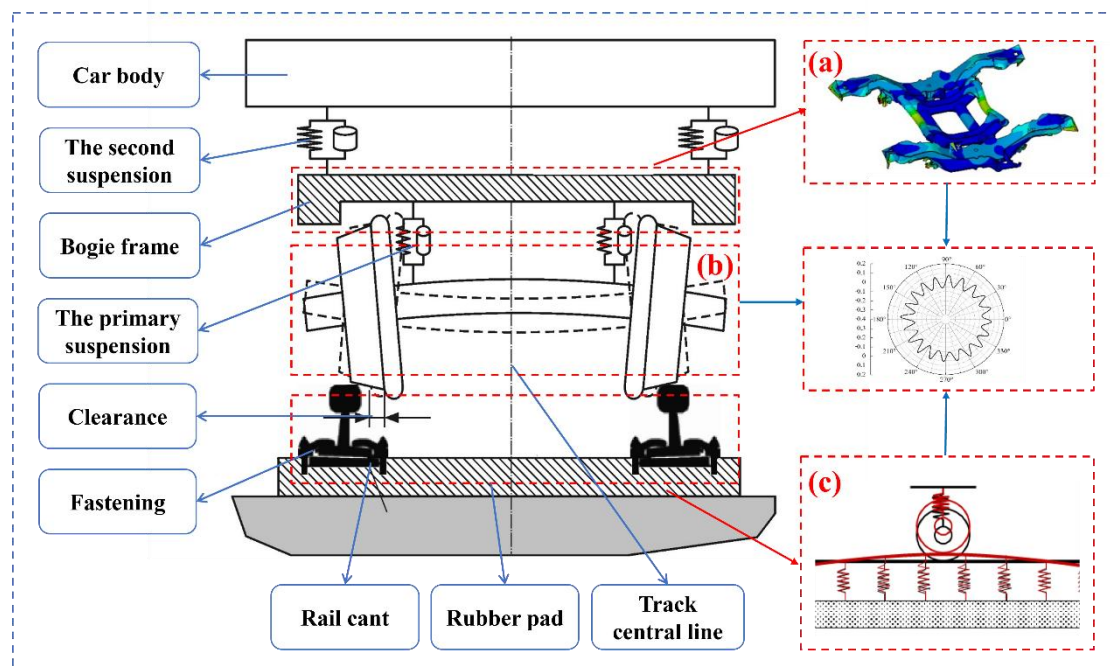


Fig. 3. Resonance-driven mechanisms proposed for wheel polygonal wear: (a) local bogie-frame resonance; (b) wheelset bending resonance; (c) track P2 resonance.

2) Friction-induced self-excited vibration

Under certain wheel-rail contact conditions, self-excited vibration at the interface is also regarded as an important cause of wheel

polygonal wear. Chen et al. [18] investigated polygonal wear formation from the perspective of friction-induced self-excited vibration in the wheelset-track system. Kang et al. [19] proposed that, when subway

vehicles negotiate small-radius curves, saturated creep force at the wheel–rail interface can trigger frictional self-excited oscillation and promote polygonal wear. Kang et al. [20], using a rigid-flexible coupled subway vehicle model for small-curve negotiation, further showed that saturated creep force on the leading wheelset can induce unstable wheel–rail oscillation and then generate polygonal wear. Zhao et al. [21] reached a similar conclusion for high-speed trains and identified friction-induced self-excited vibration in the wheel–rail system as a principal mechanism.

3) Initial-defect-triggered feedback

Tao et al. [22] found that discrete irregularities on wheel surfaces can excite wheelset vibration and then induce high-order polygonal wear. Ye et al. [23] indicated that P2 resonance triggered by wheel flats can initiate polygonal wear. Initial machining defects on wheel rims, reported by Johansson and Andersson [24], can amplify P2 resonance and may become a dominant factor in polygonal wear development. Yang et al. [25] proposed that dominant 17th- to 18th-order polygonal wear on locomotive wheels originates from initial wheel defects, and that lowering the trigger threshold of anti-slip controllers can mitigate wear progression. Taken together, the available studies indicate that local defects capable of generating persistent periodic wheel–rail impact may promote polygonal wear, which highlights the importance of prompt detection and repair.

From a monitoring perspective, the three mechanism families are associated with different signal characteristics. Cases of resonance-driven excitation are often linked to wheel–rail force variation, axle-box high-frequency acceleration, and rail strain.

Friction-induced self-excited vibration is more readily reflected in ultra-high-frequency vibration and contact acoustic signals. Initial-defect-triggered feedback is often manifested through impact force, laser profile variation, or acoustic emission. Current evidence therefore supports several plausible mechanism pathways, while also showing that a single universal explanation has not yet been established. That distinction is important for the sensing and diagnostic discussion in later sections.

3.2 Other Major Damage Modes

3.2.1 Wheel Flats

Besides polygonal wear, the main wheel damage modes include wheel flats, rolling contact fatigue (RCF), and hollow wear. Wheel flats and many RCF manifestations are strongly localised defects, whereas hollow wear is better understood as a profile-dependent damage mode distributed over a broader tread region. Although the morphology and development path differ, all three arise within the same wheel–rail contact system and may coexist in service.

A wheel flat is a common tread defect formed under abnormal braking or low-adhesion conditions, as shown in Fig. 2(b). The defect originates from severe wheel–rail friction after wheel motion departs from pure rolling, which causes local material loss [26–31]. During each wheel revolution, a flat generates wheel–rail impact force and dynamic response levels several times higher than those under normal rolling [32]. Repeated impacts produce high wheel–rail noise [26] and impose impulsive loads on critical components [31], which shortens service life. As a high-frequency tread defect, a rotating flat can also excite abnormal rail vibration. The resulting shock loads increase axle stress and may compromise axle

integrity, which creates a direct risk to running safety.

The primary hazard of a wheel flat is not the material loss itself but the periodic impact force it generates; impact peaks can reach several times the normal wheel–rail force, directly threatening the fatigue life of axles, bearings, and track components. From a monitoring standpoint, force-based and acoustic-based methods exhibit the highest sensitivity to wheel flats, whereas optical methods such as laser profilometry provide direct length and depth quantification, making them the preferred tools for confirmation. Moreover, a flat can easily trigger P2 resonance and subsequently initiate polygonal wear. Consequently, once a flat is detected, re-profiling should be prioritised.

3.2.2 Rolling Contact Fatigue (RCF)

Rolling contact fatigue (RCF) is a fatigue damage mode caused by repeated wheel–rail contact loading combined with creepage under traction and braking. Under high-wear conditions, incipient cracks may be removed before further growth, so wheel wear and RCF are often coupled through a competitive interaction [33]. The full RCF process includes crack initiation, early growth, propagation, and material separation [34]. Typical manifestations include circumferential cracks, angled cracks, transverse cracks, pitting, spalling, and shelling. Among those forms, spalling associated with crack networks is often regarded as a severe RCF state. Fig. 2(c) shows common RCF forms on wheel treads [35]. RCF may develop either as continuous damage along the contact band or as more localised damage, and the two forms are often discussed as continuous RCF and localised RCF. Continuous RCF may extend across a relatively large area of the wheel

tread. A widely cited classification framework [36] divides continuous RCF into four types according to transverse position. Type I occurs outside the nominal rolling circle. Type II appears at the flange root. Type III is characterised by transverse cracks near the nominal rolling circle. Type IV occurs between the region outside the nominal rolling circle and the straight tread section and is linked mainly to lateral creep force. In recent years, severe Type II and Type III RCF have been reported on high-power locomotives and metro vehicles in China [37].

RCF may also be classified according to crack initiation site, namely surface-initiated RCF and subsurface-initiated RCF. Wang et al. [38] further distinguished three groups according to crack origin and depth: (i) surface RCF, with crack depth of about 0.5–5 mm, associated with low-cycle fatigue or surface ratchetting; (ii) subsurface RCF, with crack depth of about 3–10 mm, associated with internal material defects; and (iii) deep-seated RCF, with crack depth of about 10–30 mm. Ekberg and Kabo [39] expressed a similar view and linked tread-surface RCF cracks to low-cycle fatigue and ratchetting. These depth ranges provide a quantitative descriptor of RCF severity and damage penetration. They should not be interpreted as a universal chronological sequence, because crack depth also depends on the initiation site, material defects, and local wheel–rail contact conditions. Nevertheless, crack depth, together with crack morphology and spalling extent, provides a measurable basis for comparing RCF evolution. This distinction also has implications for inspection: surface manifestations may be reflected in profile, strain, vibration, or acoustic responses, whereas suspected subsurface or deep-seated RCF may warrant

complementary depth-sensitive inspection, including ultrasonic methods.

From a mechanistic standpoint, the factors governing crack initiation and penetration have also been investigated. Zhou et al. [40] showed that lateral force promotes plastic deformation accumulation and aggravates RCF damage at the tread centre. Tao et al. [41] found that large creep force in specific directions during small-radius curve negotiation is a major cause of cracking and spalling on the outer tread. Zeng et al. [42] further showed that macroscopic defects in the wheel rim act as major initiation sources of subsurface RCF cracks under high stress, and that control of defect morphology can help suppress fatigue crack initiation.

3.2.3 Hollow Wear

Hollow wear refers to concave profile wear developed near the nominal rolling circle of the wheel tread, as shown in Fig. 2(d). Severe hollow wear modifies the original wheel profile, changes wheel–rail contact geometry, and can induce abnormal bogie vibration [43]. Wang et al. [44] found that abrasive block action and low-pressure intermittent working modes can influence hollow-wear development and help maintain equivalent conicity. Qi et al. [45] investigated hollow wear from the perspective of wheel–rail contact probability distribution using a wheel wear index, showing that uneven contact-position distribution is an important cause of tread concavity. Wang and Gong [46], through wheel-profile and frame-vibration tracking, further showed that hollow-wear evolution can reduce vehicle stability and increase lateral vibration.

The mechanism of hollow wear remains less clearly established than those of polygonal wear and wheel flats, but recent studies have clarified several important consequences.

Zhou et al. [47] showed that double-hollow worn wheel profiles can reduce equivalent conicity and induce abnormal low-frequency lateral vibration of the car-body. Wang et al. [48] found that hollow wear may also affect wheel–rail adhesion under wet conditions through changes in contact state. Because hollow wear is mainly reflected in profile geometry and hunting-related dynamic response, wheel-profile measurement, optical or laser profile inspection, and fibre-optic response monitoring can provide useful evidence for assessment. Overall, hollow wear links local tread-profile evolution with contact-geometry change, interfacial condition, equivalent conicity, and vehicle dynamic response.

The formation of different damage modes involves strong coupling across factors and scales. Although polygonal wear, wheel flats, RCF, and hollow wear have been discussed separately above, they may interact during service. Wheel flats can generate periodic wheel-rail impact and trigger P2 resonance, thereby initiating or aggravating polygonal wear [23]. Wheel wear and RCF also show a competitive relation, because material removal may eliminate shallow surface cracks, whereas insufficient wear may allow cracks to accumulate under repeated contact loading [33]. Hollow wear changes wheel profile geometry and equivalent conicity, which can induce hunting motion and further modify wheel-rail contact conditions [43–45]. These coupling paths indicate that wheel damage should be interpreted not only through individual defect mechanisms, but also through the ways in which one damage mode changes the initiation, growth, or monitoring characteristics of another.

Research on mechanisms and influencing factors provides the basis for wheel condition monitoring, wear prediction, and safe

railway operation. As summarised in Table 2, wheel damage does not arise from a single universal mechanism, but from different combinations of structural resonance, frictional instability, local defect feedback, material response, and contact-condition evolution. The four damage modes also differ in observability: wheel flats are mainly reflected by impulsive responses, polygonal wear by order-related dynamic features, RCF

by crack and fatigue indicators, and hollow wear by profile- and stability-related responses. These differences explain why no single monitoring or prediction approach is sufficient for all damage modes. Once the main damage modes and formation pathways are clarified, the next question is which material, operational, and environmental factors govern their initiation, competition, and long-term evolution.

Table 2. Representative wheel damage modes, underlying mechanisms, signal manifestations, typical monitoring approaches, and key engineering implications.

Damage mode	Dominant mechanism	Sensitive signals	Representative monitoring approaches	Key engineering implications
Polygonal wear	Resonance-driven excitation (wheelset/track/P2/bogie frame)	Wheel-rail force, axle-box high-frequency acceleration, rail strain	Force-based methods; vibration analysis	Speed adjustment can break resonance locking; high-order wear → check bogie-frame resonance first
	Friction-induced self-excited vibration	Axle-box ultra-high-frequency vibration, contact acoustic signal	Acoustic-based methods; high-frequency vibration analysis	Dominant in locomotives on tight curves; use broadband vibration sensors
	Initial-defect-triggered feedback	Impact force, laser profiling, acoustic emission (AE)	Optical-based methods; impact-response detection	Prompt detection of initial defects prevents feedback growth
Wheel flat	Wheel sliding & periodic wheel-rail impact	Impact force, axle-box acceleration, impact acoustic signal	Force-based, acoustic-based, and optical-based methods	Once detected, re-profile urgently—wheel flats can trigger P2 resonance and polygonal wear
RCF	Repeated contact load, ratchetting, subsurface inclusions	Strain, AE, vibration, and ultrasonic response	Force-based monitoring, AE monitoring, and ultrasonic inspection	Surface manifestations: indirect profile, dynamic, or acoustic evidence; suspected deep-seated RCF: complementary ultrasonic inspection.

Hollow wear	Non-uniform wheel-rail contact (mechanism unclear)	Wheel profile geometry, bogie vibration response	Optical-based methods; vibration analysis	Priority: establish conicity-based early warning; physical model development is secondary

4. Factors Governing Wheel

Damage Evolution

Wheel damage in service is not governed by any single parameter. Instead, damage evolves through coupled interactions among wheel–rail material properties, contact mechanics, operating conditions, and

environmental or interfacial effects [49]. Some factors act directly on contact stress and creepage, whereas others alter friction, thermal state, or the balance between wear and fatigue. The discussion in this section therefore focuses on four factor groups: wheel–rail hardness matching, material properties and material matching, operational conditions, and environmental or interfacial conditions. Fig. 4 summarises that framework.

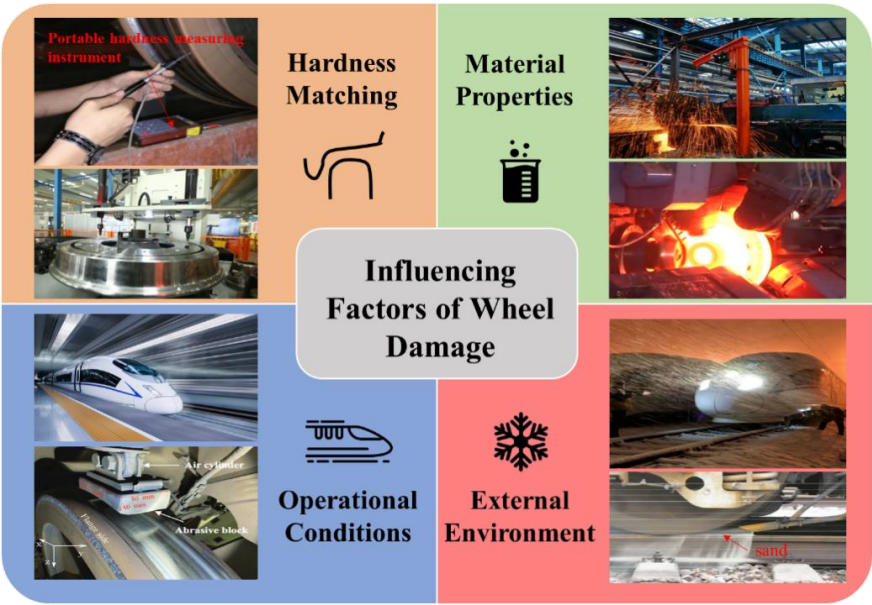


Fig. 4. Main factors influencing wheel damage.

4.1 Wheel-Rail Hardness Matching

The wheel–rail hardness ratio has a direct effect on contact stress and therefore on wheel wear. Higher hardness often reduces wear rate, but hardness cannot be increased without limit because loss of toughness may increase fatigue risk. Santa et al. [50] found that an R400HT rail and E8 wheel pairing gives a lower wear rate, associated with a higher wear-transition energy threshold, and

that fatigue crack initiation also becomes more difficult under humid conditions. Shen et al. [51] showed that non-uniform wheel hardness can aggravate polygonal wear, whereas improved hardness level and hardness uniformity through roller hardening can suppress wear development.

Wheel hardness alone is not sufficient for assessment, because matching between wheel and rail is also important. Chang et al.

[52] showed in wear tests that a wheel–rail hardness ratio below 1.05 tends to promote polygonal wear, whereas a ratio above 1.36 can suppress wear growth. Hu et al. [53] found that higher wheel hardness reduces wheel wear rate, and that rail wear rate can also decrease under some conditions. Further work [54] indicated that wheel wear rate decreases as the wheel–rail hardness ratio increases, whereas rail wear shows the opposite trend.

No single optimum hardness ratio has yet been established, which means that suitable hardness matching still needs to be defined for different service conditions. Hardness matching, however, represents only one aspect of wheel-rail material design. Material composition, microstructure, strength, and toughness also shape wear and fatigue behaviour and therefore need to be considered alongside hardness.

4.2 Material Properties and Material Matching

Improved hardness uniformity, a moderate increase in wheel hardness, and control of the wheel–rail hardness ratio within a suitable range of about 1.1 to 1.4 have been reported as effective measures for suppressing polygonal wear, reducing overall wear level, and delaying RCF. Material composition, however, also governs strength and toughness and must therefore be considered alongside hardness rather than in isolation. Cantini and Cervello [55] showed through full-scale tests that high cyclic yield strength and fracture toughness inhibit crack propagation and reduce crack depth. Ueda [56] found that higher carbon content in

pearlitic steel reduces spalling and crack depth while increasing surface hardness and suppressing plastic flow. Jia et al. [57] identified an optimal carbon range of 0.69%–0.74% for balancing strength and toughness in high-speed and heavy-haul wheel steels. Excessive Si, Mn, or alloying additions such as Cr, V, Ni, or Mo can increase strength but may also reduce impact toughness.

Chen et al. [58] showed that increasing wheel carbon content and hardness raises the wheel–rail hardness ratio and reduces wheel wear, but may aggravate deep rail spalling and promote internal fatigue crack growth in the rail, thereby shortening rail life. Zhou et al. [59] showed through finite-element modelling that strain-rate hardening increases contact stress while suppressing plastic deformation, whereas initial fatigue damage reduces contact stress but promotes plastic flow. Neither effect changed adhesion markedly, because adhesion remained governed mainly by traction and friction.

Material design has moved from qualitative discussion towards more quantitative control of hardness matching, microstructure, and damage resistance. Table 3 summarises representative thresholds and reported effects of wheel–rail hardness ratio and carbon content on service behaviour and provides a useful basis for material selection. Even so, material properties alone cannot account for the evolution of wheel damage in service. Damage progression also depends on operating conditions, environmental exposure, and interfacial effects, all of which modify contact state and the balance among wear, impact, and fatigue.

Table 3. Representative material parameters and reported implications for wheel damage evolution.

Factor	Representative range or finding	Reported effect	Typical application condition
Wheel-rail	<1.05; >1.36; 1.1–1.4	Below 1.05 promotes	General wheel-rail systems

hardness		polygonal wear; above	
ratio		1.36 suppresses wear;	
		1.1-1.4 has been reported	
		to inhibit polygonal wear	
		and delay RCF	
Carbon	0.69%–0.74%	Achieves balance	
		between strength and	
		content	
		toughness	
		High-speed and heavy-haul wheel	
		steels	

4.3 Operational Conditions

During service, trains do not operate under ideal conditions, and operating states often depart from nominal targets. Typical cases include high-speed traction, emergency braking, speed variation, initial wheelset installation deviation, and brake block interaction. Under traction and braking, wheel-rail interaction forces can change sharply, which may accelerate both the initiation and growth of wheel damage. Sang et al. [60] found that higher braking intensity increases longitudinal creep force and aggravates wheel wear. Larger line gradient also increases wear, whereas a higher wheel–rail friction coefficient reduces wear. Tang et al. [61], using finite-element analysis, showed that traction-induced saturated creep force can excite specific wheel modes and trigger high-order polygonal wear. Temperature rise under severe braking can further accelerate deterioration. Lu et al. [62], in research on copper-based powder-metallurgy brake blocks, showed that wear rate rises at high temperature and that the dominant wear mechanism shifts from abrasive wear to oxidative wear and then to adhesive wear as temperature increases.

Operating speed is also a key parameter in the competitive relation between wheel wear and RCF. Sang et al. [63] pointed out that motor cars and trailers can exhibit different wear rates during acceleration, and that wear and RCF respond differently to speed variation. He et al. [64], through simulation,

found that increasing speed reduces wheel surface hardness and wear rate but intensifies RCF damage, which further confirms the competitive relation between wear and fatigue. Heng et al. [49], based on a vehicle dynamics model, quantified that operating speed and wheel-rail friction coefficient is positively correlated with wear, whereas curve radius is negatively correlated with wear.

Initial wheelset installation condition is another important source of non-uniform wear. Ding and Li [65] showed that initial installation yaw angle strongly affects wheelset yaw motion, whereas wheel diameter difference mainly affects lateral displacement. Both factors can induce severe uneven wear. Under combined yaw angle and wheel diameter difference, larger tread equivalent conicity can mitigate tread wear. Brake blocks were introduced during train development to remove third-body media such as leaves and snow from railhead surfaces. Engineering observations later suggested an additional role in suppressing wheel damage development. Ma et al. [66], through tracking tests, showed that brake block fitting on metro vehicles does not change the near-linear growth trend of tread wear, but can suppress polygonal wear and uneven lateral pitting, reduce equivalent conicity, and decrease flange wear.

The available studies show that operational conditions influence both damage initiation and the later balance among wear, impact,

and fatigue. High-speed traction, emergency braking, speed variation, wheelset installation deviation, and brake block interaction all alter wheel–rail creep force, friction, and thermo-mechanical response. Those changes shape the overall evolution of wheel damage under complex service conditions.

4.4 Environmental and Interface Conditions

Environmental conditions strongly influence both the occurrence and development of wheel damage. Wheel-rail behaviour is governed not only by direct mechanical interaction but also by coupled environmental effects. Railway operation spans plains, high-altitude cold regions, mountainous areas, and desert regions, and each setting introduces distinct challenges for wheel damage control. Environmental effects act chiefly through temperature change and third-body media, as illustrated in Fig. 5.

Temperature directly affects wheel material behaviour and is an important trigger for transitions in wear mechanism. Shen et al. [67], through wheel wear tests under simulated severe cold conditions, showed that low temperature promotes a shift from abrasive and oxidative wear towards fatigue-dominated wear. Ma [68], based on low-temperature wheel–rail wear tests, found that as temperature falls, wheel–rail friction coefficient, wear rate, and surface hardness first increase and then decrease slightly, which further modifies damage evolution.

In addition to temperature, third-body media at the wheel-rail interface, including dry and

wet leaves, sand particles, and oil films, alter damage behaviour by changing friction level. Shu et al. [69] showed that, in a wind-sand environment, higher sand flow rate can reduce slip ratio and slow wear and fatigue damage progression, mainly because sand particles provide buffering and interfacial separation. Gallardo-Hernandez and Lewis [70] quantified the effects of oil, leaves, and sand particles and found that oil, water, and dry leaves reduce adhesion coefficient and can increase braking distance, whereas sanding can improve adhesion but may also cause severe wheel surface damage. Ma et al. [71], based on a wheel-rail contact test rig, showed that water, oil, and leaves reduce maximum friction coefficient, whereas quartz sand increases it. Mixed-media effects are often weaker than the effect of a single dominant medium.

Environmental and interface conditions should be interpreted not only as factors affecting wheel damage, but also as controllable variables for damage mitigation. Temperature-sensitive assessment is needed because low temperature can modify wheel material behaviour and shift the wear mechanism. For third-body media, controlled sanding can improve adhesion under low-adhesion conditions, although excessive sand particles may also intensify abrasive wear and surface damage [69-71]. Friction modifier application and oil-film management can regulate the friction level at the wheel-rail interface and may reduce wear, noise, and frictional instability. In addition, brake block and abrasive block action can remove dry and wet leaves, snow, and other third-body media, thereby helping to control wheel wear evolution and wheel-rail contact conditions.

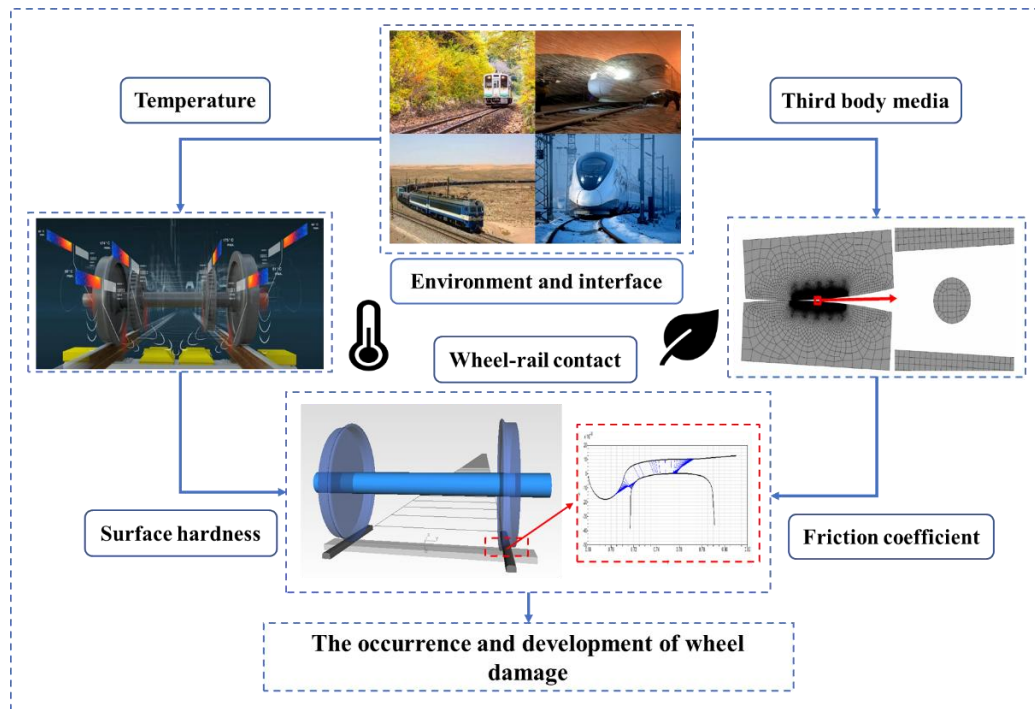


Fig. 5. Influence of environmental and interface conditions on wheel-rail contact and wheel damage.

Overall, the reviewed literature does not support a single dominant factor for all wheel damage scenarios. Damage evolves through coupled changes in contact geometry, creepage, friction, thermal state, and material response. Several cross-cutting observations are particularly important: speed can reduce wear rate but intensify RCF [64], hardness-ratio selection involves trade-offs between suppressing polygonal wear and limiting rail damage [52], low temperature may shift wear towards fatigue-dominated behaviour [67], and third-body media can either reduce adhesion or accelerate surface damage [70-

71]. These interactions show why single-factor interpretation is insufficient and why prediction models require multi-factor calibration and field validation. Practically, hardness-ratio thresholds, speed-dependent wear-RCF competition, and environmental effects can inform material selection, monitoring priorities, and maintenance triggers. Because these coupled effects must ultimately be inferred from measurable force, vibration, acoustic, optical, and profile-related responses, the next section turns to monitoring and diagnostic evidence.

comfort. Timely condition monitoring is therefore essential.

5. Monitoring and Diagnostic

Evidence for Wheel Damage

In service, progressive wear alters wheel-rail contact conditions and degrades operational performance. Wheel wear can increase impact force [72], excite vehicle and track resonances [73-75], aggravate vibration and noise, and may induce running instability, directly compromising safety [76] and ride

Wheel fault diagnosis relies on two complementary routes: bench testing and in-service monitoring. Controlled experiments and field observations link damage evolution to measurable responses, including force, vibration, strain, acoustic emission, and geometric variation. This section reviews the diagnostic evidence provided by each method for mechanism interpretation, model calibration, validation, and maintenance

decision-making.

5.1 Bench Testing and Controlled Experimental Evidence

In wheel–rail damage research, bench testing provides an essential basis for theoretical validation and controlled empirical analysis. When wheel flats, polygonal wear, or spalling are detected in service, immediate re-profiling is often required, making continuous pre-intervention signal histories unavailable. Bench tests can reproduce severe contact states and operating scenarios that are difficult to capture on open lines, enabling detailed study of damage initiation, evolution, environmental effects, and wear-induced changes in vehicle dynamic performance.

Lin and Liu [77] reviewed wheel–rail dynamic responses caused by tread defects and showed that most test rigs use wheel-on-wheel rolling contact to approximate wheel–rail interaction, whereas a smaller number of platforms use wheel-on-rail rolling contact to reproduce coupled behaviour between a real wheel and a rail. For comparison between

wheel-on-wheel and wheel-on-rail configurations, Yan et al. [78] analysed the relation between both rig types and real wheel–rail coupled dynamics and indicated that wheel-on-rail rigs reproduce in-service conditions with greater realism. Wheel-on-wheel rigs, however, require less installation space and suit long-duration tests of wheel–rail coupled interaction. Bench tests are therefore used widely to analyse system coupling, material response, and the influence of wheel wear on train dynamics, and they provide an important experimental basis for understanding and comparing wear-prediction theories.

5.1.1 Wheel-on-Wheel Rolling Contact Simulation

Wheel-on-wheel rolling contact simulation is a laboratory approach that mainly uses twin-disc or twin-roller rigs to investigate wheel–rail interaction. Research in this area has focused on material pairing, interfacial media, operating parameters, and model calibration. The resulting data therefore provide an important basis for mechanism analysis and wear prediction.

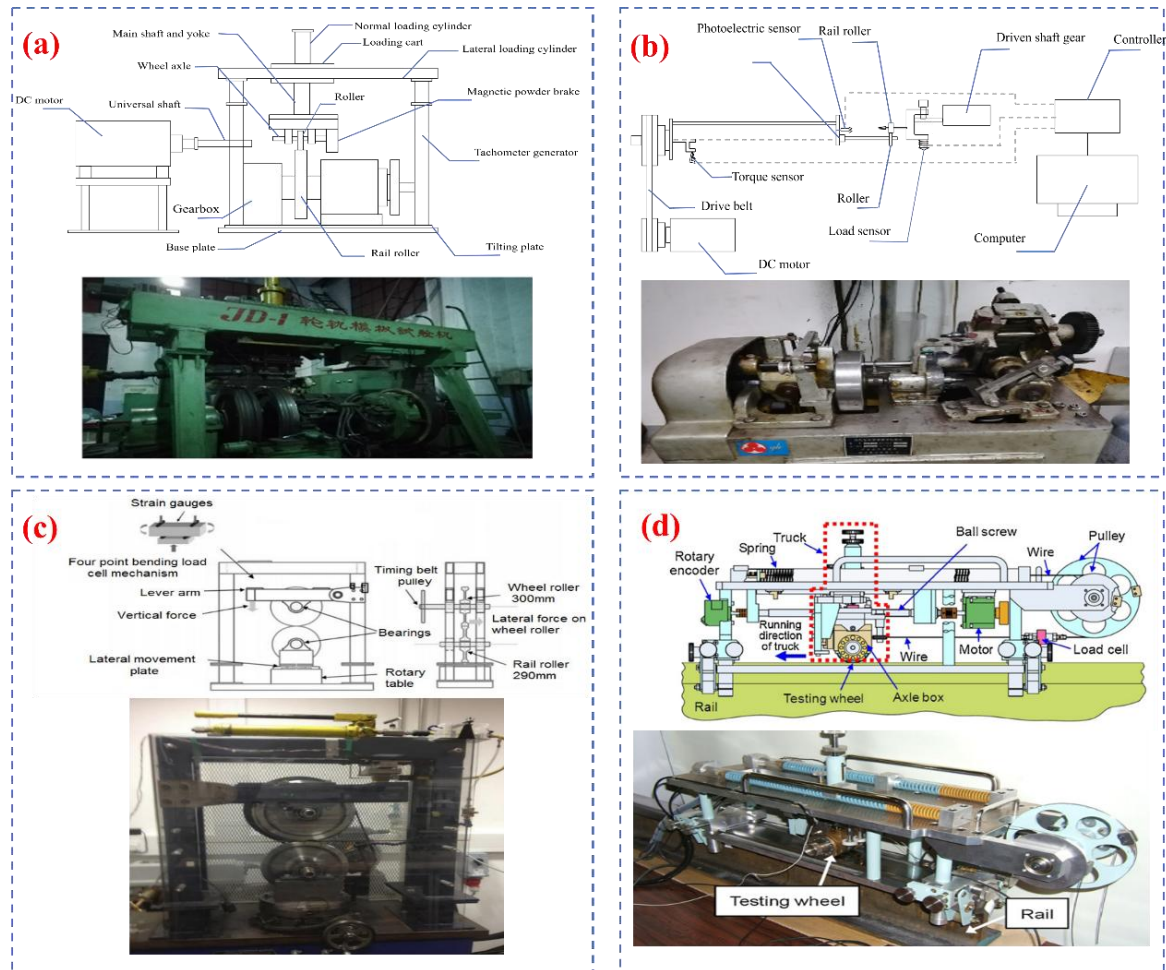


Fig. 6. Representative bench-test rigs: (a) JD-1 testing device [40]; (b) MMSA-2A testing device [86]; (c) twin-disc testing device [87]; (d) creep testing device [89].

Material properties are a key factor in wheel–rail interaction, and simulation tests reveal damage mechanisms under different pairings, supporting material selection and service-life improvement. Zhou et al. [40] used the JD-1 wheel–rail simulation device (Fig. 6(a)) with SEM and hardness measurements to analyse tread damage under varying lateral force. Cantini and Cervello [55] evaluated RCF behaviour of two wheels materials on the full-scale BU300 rig under controlled vertical load and yaw angle. Chen et al. [58] conducted rolling contact tests on an MMSA-2A machine for four wheels materials with different carbon contents paired with U75V rail, analysing the effect of hardness ratio on wheel damage. Chang et al. [52] and Zhang et al. [79] investigated hardness matching

across nine wheel–rail combinations on an Amsler wear machine, demonstrating that higher wheel hardness reduces wear and suppresses polygonal wear development. Santa et al. [50] studied wear-mechanism transition and RCF behaviour for an R400HT rail–E8 wheel pairing through twin-disc tests. Collectively, these studies establish that both material pairing and hardness matching profoundly influence wear rate, wear-mechanism transition, and RCF susceptibility, providing a quantitative basis for selecting wheel–rail material combinations.

Operating speed and environmental conditions are also key variables in wheel–rail damage evolution. He et al. [64] found

that increasing speed reduces wheel surface hardness and wear rate but intensifies RCF severity, indicating a clear wear–RCF competition. Li et al. [80] demonstrated strong temperature dependence in friction modifier performance. Zhou et al. [81] and Bai et al. [82] investigated temperature and airflow effects, showing that low temperature reduces wheel wear but increases rail wear, accelerates plastic deformation and work hardening, and promotes fatigue crack initiation. Ma [68] compared RCF behaviour at room and low temperatures, reporting ploughing-dominated damage at room temperature versus fatigue cracking and spalling at low temperature. These findings indicate that operating speed modulates the wear–RCF balance and that low temperature shifts the dominant wear mechanism from oxidative and abrasive modes towards fatigue-dominated damage, providing direct guidance for condition-based maintenance under different service environments.

Third-body media, including interfacial contaminants, can markedly alter contact state and damage mechanisms. Gallardo-Hernandez and Lewis [70] showed through twin-disc tests that oil, wet and dry leaves generally reduce adhesion, whereas sanding improves adhesion but may induce surface damage. Faccoli Michela et al. [83] and Wang et al. [84] further demonstrated the damaging effects of desert sand, water, oil, and fallen leaves on wheel steels under low-adhesion conditions. Shen et al. [85] simulated warm humid airflow intrusion at -40°C and found that fatigue damage dominates in dry conditions, whereas intermittent moisture promotes oxidative and adhesive wear. Collectively, these studies indicate that third-body media exert highly condition-dependent effects—either reducing adhesion and compromising

braking safety, or accelerating surface damage and material loss—and that their interactions with temperature and humidity further complicate damage prediction, reinforcing the need for environment-specific monitoring strategies and hybrid models that incorporate interfacial variables.

Experimental data also support the construction and calibration of wear-prediction models. Butini et al. [86] developed an integrated numerical framework for combined wear and RCF prediction, validated on MMSA-2A (Fig. 6(b)) and JD-1 test rigs. Braghin et al. [87] established a piecewise linear wear model based on frictional work from twin-disc tests (Fig. 6(c)), achieving a tread wear prediction error of approximately 5% on a full-scale rig. Shebani and Iwnicki [88] applied a neural-network model to twin-disc wear data under different media conditions, using contact load, motion parameters, and geometric inputs to predict accumulated wear. These studies illustrate a clear progression from purely physics-based approaches towards data-driven and hybrid approaches, demonstrating that experimental data serve not only for model calibration and validation but also as training sources for machine learning methods, thereby bridging controlled laboratory evidence and predictive maintenance applications.

In summary, wheel-on-wheel rolling contact tests provide controlled experimental evidence for mechanism analysis, material matching, parameter calibration, and wear-model development. The main strength of the method lies in repeatability and controllability, whereas the main limitation lies in simplified geometry and boundary conditions, which can reduce direct representativeness of full in-service behaviour.

5.1.2 Wheel-on-Rail Rolling Contact Simulation

Wheel-on-rail rolling contact simulation establishes direct contact between a wheel and a rail under laboratory conditions, rather than using two rollers to approximate wheel–rail interaction. Because contact geometry and structural response are represented more directly, the approach is valuable for analysing wheel behaviour on track. Larger space and equipment requirements, however, mean that wheel-on-rail platforms remain limited.

Doi et al. [89] developed a device for creep characteristic testing between wheels and rails, shown in Fig. 6(d), allowing a real wheel to roll on a rail. Su et al. [90] established a vehicle–track rigid-flexible coupled dynamics model with a flexible wheelset using SIMPACK and ANSYS, acquired axle-box acceleration signals under different speeds and wheel flat depths, and verified data reliability with a 1:1 single-wheel rolling test rig. Yamashita et al. [91] developed a wheel tread profile optimisation procedure that incorporates wear evolution to minimise flange wear. Their framework integrates wear simulation into profile optimisation, and scaled roller-rig experiments showed good agreement between simulation and test data. The procedure reduced both flange wear and tread damage during long-distance running.

Wheel-on-rail rigs have increasingly been

used for targeted experiments on wheelset wear and wheel–rail contact evolution, and therefore provide a closer experimental link between laboratory simulation and prediction research. Field measurements, however, provide direct damage-related data under real operating conditions. Because many complex service scenarios cannot be reproduced repeatedly on open lines, laboratory and field evidence should be treated as complementary sources of diagnostic information rather than as competing alternatives.

5.2 In-Service Monitoring and Diagnostic Evidence

Most methods for monitoring train dynamic loads rely on direct measurement through sensors mounted on the track or on the wheelset, although some studies use indirect measurement from other vehicle or infrastructure locations [92]. Onboard monitoring uses sensors on wheelsets or axle boxes to acquire strain and acceleration signals, but fleet-wide coverage of wheel–rail contact conditions is difficult unless every train is instrumented. For large-scale detection of operational safety, running stability, and wheel faults, wayside systems remain the more economical and practical option. Fig. 7 shows representative sensor layouts for onboard and wayside schemes. In the following discussion, in-service monitoring methods are grouped into force- and vibration-based, acoustic-based, and optical-based methods.

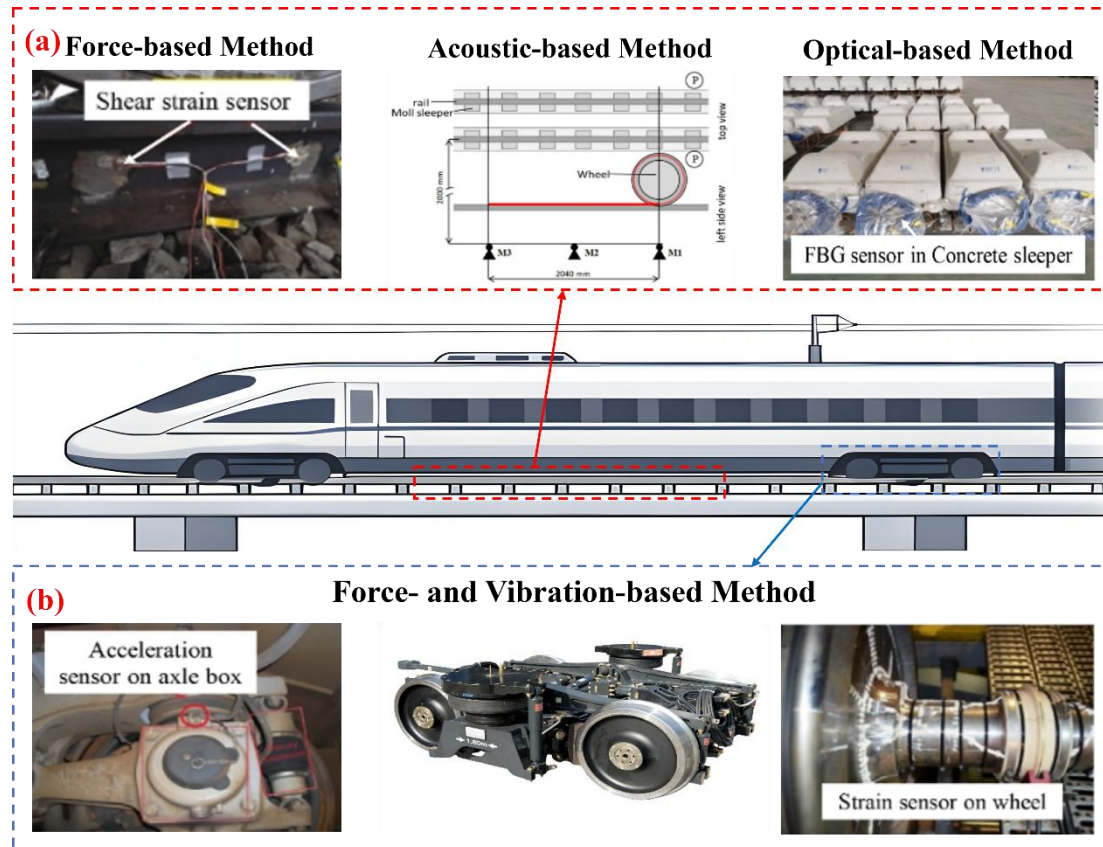


Fig. 7. Representative sensor locations in onboard and wayside monitoring schemes.

5.2.1 Force- and Vibration-Based Methods

Wheel–rail force is a key indicator of interaction in the vehicle–track coupled system, with force level and fluctuation directly linked to running safety and stability. Diagnostic work in this area has been particularly relevant to polygonal wear and wheel flats, with research progressing from model-based feasibility studies to field sensing practice and vibration-based assessment.

Model- and simulation-based studies have first assessed the feasibility of wheel condition evaluation from force signals. Liu and Zhai [93] used a vertical vehicle–track coupled dynamics model to identify clear time- and frequency-domain fluctuation characteristics induced by polygonal wheels, supporting force-based diagnosis of typical wheel defects. Jin et al. [7] further combined

field axle-box vibration data with a vehicle–track dynamics model, correlating dominant vertical axle-box acceleration components with polygonal passing frequency and establishing first-order wheelset bending resonance as an important mechanism in polygonal wear formation.

Building on this theoretical foundation, sensing practice has developed both onboard and wayside measurement solutions. Dong et al. [72] adopted an indirect wheel–rail force measurement method based on strain gauges mounted on the rail and on an instrumented wheelset, including the wheel web and hub, with rotating signal transmission through slip rings. Gauge layouts are shown in Fig. 8(a) and Fig. 8(b). Wheel–rail force is obtained through strain measurement and inverse calculation on the wheel web and hub. Acceleration sensors are mounted above the axle box, and axle strain sensors are mounted

at Section B on the inner arc of the wheel seat, as shown in Fig. 8(c) and Fig. 8(d). Because wheelsets are rotating components, slip rings are used for wheel–rail force and axle-stress signal transmission, as shown in Fig. 8(e). Continuous measurement is implemented with a dedicated data-acquisition system, shown in Fig. 8(f). Wayside monitoring systems have been developed in parallel: Feng and Zhang [94] introduced a safety monitoring system using vertical and bidirectional plate sensors for real-time wheel–rail force and vehicle state identification; Zhang et al. [95] converted under-rail pads into load sensors; and Li et al. [96] extended force- and strain-based approaches to slab-track infrastructure through embedded fibre-optic sensing.

Train condition assessment may also be derived from vibration response rather than direct wheel–rail force measurement. Wang et al. [97] investigated vibration characteristics of heavy-haul freight wagons

and quantified the effects of wheel diameter difference through full-vehicle tests, thereby providing a data basis for fault diagnosis. Jiang et al. [43], in work on abnormal vibration in metro vehicles, carried out comprehensive tests on car-body, bogie, and axle-box vibration. Combined analysis with a coupled dynamics model clarified the mechanism by which hollow wear can induce hunting motion.

Force-related diagnosis therefore includes model-based simulation, direct measurement, and indirect inversion. Conventional rail-mounted strain-gauge methods still face challenges in gauge positioning and response extraction, but useful information can also be obtained through equivalent irregularity simulation or indirect inference from axle strain and wheel-web strain. Such signals provide a practical basis for separating healthy and damaged states and for subsequent intelligent diagnosis.

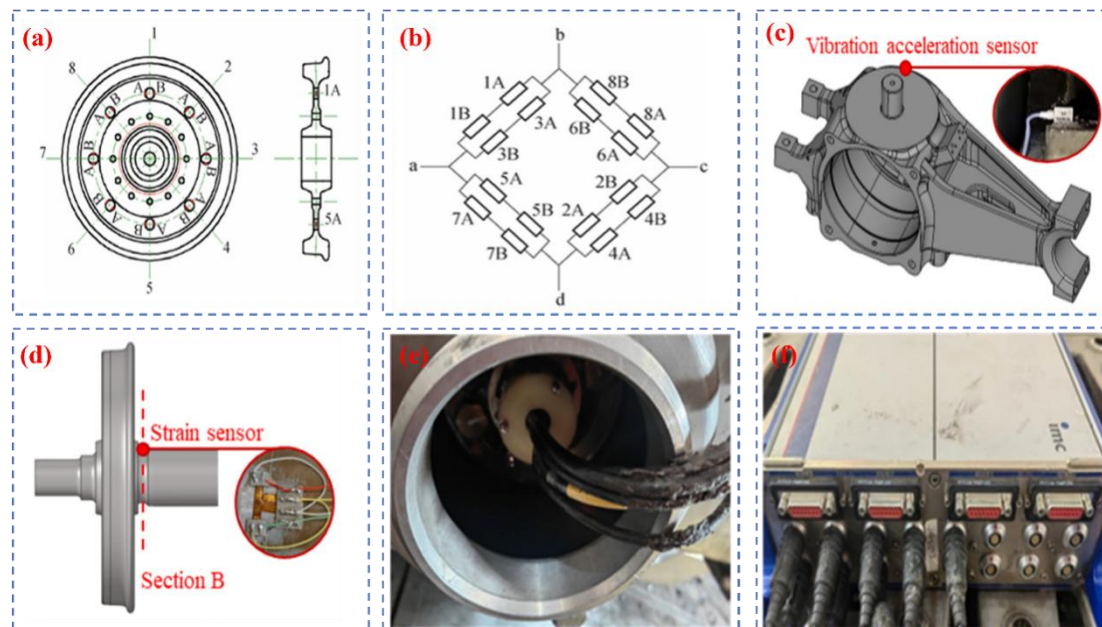


Fig. 8. Indirect wheel–rail force measurement and multi-source sensing layout [72].

5.2.2 Acoustic-Based Methods

Under healthy conditions, wheel-rail interaction generates relatively stable and

repeatable acoustic signatures. Wheel damage disrupts contact regularity and introduces abnormal vibration and acoustic response. Wheel damage can therefore be

identified through acquisition of sound-related signals followed by signal processing and feature extraction. Acoustic methods remain attractive because installation is simple, but accuracy can be limited by environmental noise, interference from adjacent wheels, and weak quantitative capability in some deployment scenarios.

Komorski et al. [98] identified wheel-flat damage through monitoring of wheel-rail impact noise during operation. Fig. 9(a) shows the acoustic acquisition arrangement used to monitor flat-induced acoustic signals. Three microphones were placed along one side of the track with spacing of 2.04 m, equal to tram wheel circumference, so that one full wheel rotation could be captured over the array length and flat-induced acoustic responses could be recorded with phase consistency. A transmitter–receiver photocell was installed between the rails for cross-section reference measurement. Acoustic signals were processed through joint time–frequency analysis, including short-time Fourier transform and wavelet transform, for tram wheel-flat detection. Follow-up work showed that reducing the number of measurement points can lower system cost [99].

The improved system configuration processes acoustic signals using Fourier transform and Hilbert transform. Diagnostic parameters are estimated from the second and third rotational harmonic components of

wheel response. Highest sensitivity was achieved at 13 to 15 dB. Aktas et al. [100] mounted acoustic emission sensors on rails through magnetic fixtures for continuous acquisition of acoustic vibration during train operation. A wheel-flat detection algorithm based on parameter-constrained optimisation was proposed, with tread condition determined by comparison between the measured defect-score curve and a predefined threshold curve. The method enabled effective flat detection across different operating speeds, with peak detection accuracy of 90%. Cavuto et al. [101] proposed a laser-ultrasonic diagnostic procedure for wheel inspection, supported by a finite-element model of ultrasonic wave propagation in wheels. The method uses air-coupled ultrasonic probes to receive laser-generated ultrasonic waves, and both laser source and receiving probe can be installed on the wheel. Zhou et al. [102] installed an ultrasonic array sensor on the rail web, as shown in Fig. 9(b), to detect wheel–rail contact stress and obtained a contact-stress distribution map on the rail, which provides support for wheel tread condition assessment. Environmental noise remains a persistent challenge in acoustic-based wheel damage monitoring and can reduce identification reliability. Even with that limitation, acoustic methods retain practical value because of simple installation and relatively low deployment burden.

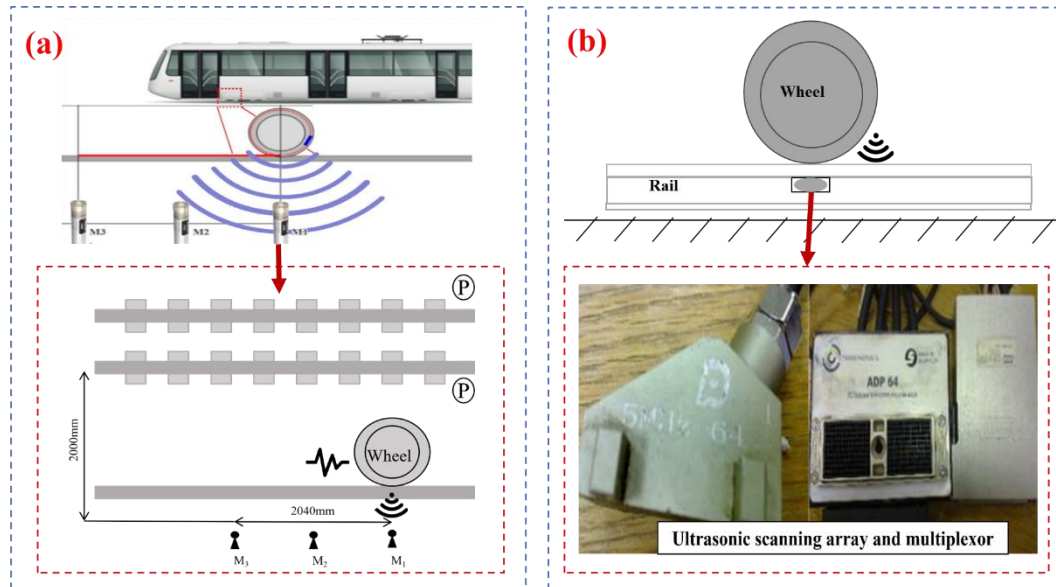


Fig. 9. Acoustic and ultrasonic detection systems for wheel damage: (a) acoustic acquisition layout [98]; (b) ultrasonic array layout [102].

5.2.3 Optical-Based Methods

Optical sensing has been widely explored for train wheel condition monitoring. Optical methods detect geometric or mechanical variation associated with wheel-rail interaction through non-contact measurement or embedded optical sensing and thereby support detection and assessment of wheel damage.

Laser- and position-sensing-based systems can obtain wheel-rail force proxies or track deformation responses by measuring optical-path variation. Gao et al. [103] developed a reflective optical position sensor system, with the operating principle shown in Fig.

10(a). The system monitored vertical movement of the rail web under wheel-rail impact and inferred wheel-flat characteristics from optical response. Cavuto et al. [101] and Zhou et al. [102] extended optical measurement to laser ultrasonics and ultrasonic reflectometry, respectively. Emoto et al. [104,105] developed laser- and image-based systems for wheelset inspection and dimensional assessment. Yang [106] proposed a laser position-sensitive detector system that uses track dynamic response to measure spot displacement on a position-sensitive detector and calculate rail bending deflection, providing an indirect indicator of wheel damage level.

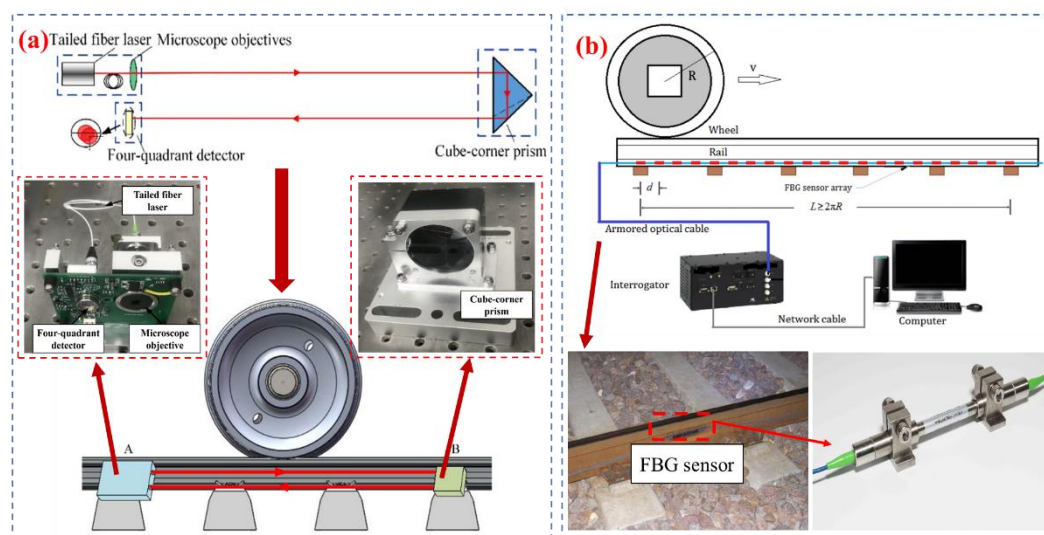


Fig. 10. Optical sensing systems for train wheel condition monitoring: (a) laser-sensor detection system [103]; (b) FBG monitoring system [108].

In addition to laser sensors, Fibre Bragg Grating (FBG) sensors have also been applied to wheel condition monitoring. FBG sensing relies on the relation between Bragg wavelength shift in the reflected spectrum and variation in external physical quantities such as strain and temperature [107]. Compared with strain gauges and acoustic sensors, FBG systems require no electrical power wiring at sensing points and show strong resistance to electromagnetic interference, which supports acquisition of high-quality operational data.

FBG sensors can be mounted on rails, and the resulting dynamic strain during vehicle passage can be analysed for wheel condition assessment, as shown in Fig. 10(b). Liu et al. [108] developed a wayside FBG monitoring system and, combined with a Bayesian blind-source separation method, achieved sensitive detection of minor wheel defects in high-speed trains. Roveri et al. [109] and Wang et al. [110] further demonstrated that fibre-optic and Bayesian forecasting methods can support real-time wheel condition monitoring under field conditions. Optical sensing technologies, particularly laser- and FBG-based methods, provide

stable routes for wheel condition monitoring, with non-contact or quasi-distributed sensing capability and applicability across a wide speed range. Existing studies have demonstrated detection of wheel flats and wheel out-of-roundness, including polygonal wear. Future work should focus on establishing quantitative relations between signal features and defect type or severity, so that diagnostic accuracy and practical applicability can be improved further.

Current monitoring studies show that no single sensing principle covers all damage modes. Force- and vibration-based methods are sensitive to impact and dynamic amplification. Acoustic methods are useful for impulsive defects but vulnerable to environmental noise. Optical methods provide stable geometric or strain-related information but often require more demanding deployment conditions. Table 4 compares these method categories in terms of their main evidence, sensitive targets, engineering role, and main limitation, while recognising that different manifestations of the same damage mode may be observable through more than one monitoring principle. Monitoring evidence should therefore be

interpreted together with mechanism understanding and modelling purpose. Bench testing provides controlled evidence for mechanism validation and parameter calibration, whereas in-service monitoring captures operational variability, damage progression, and data drift under real

conditions. The next section reviews how such evidence supports prediction approaches, while also noting that the most mature predictive studies still focus more on wheel wear than on the full range of wheel damage.

Table 4. Comparison of representative wheel damage monitoring principles

Monitoring principles	Main evidence	Sensitive targets	Engineering role	Main limitation
Force- and vibration-based methods	Force, strain, axle-box or bogie vibration	Polygonal wear, wheel flats, hollow wear, and indirect RCF-related dynamic response	Supports resonance/impact diagnosis and model validation	Sensitive to sensor layout; severity inversion remains difficult
Acoustic-based methods	Impact noise, acoustic emission, ultrasonic response	Wheel flats, RCF-related acoustic-emission response, and suspected subsurface or deep-seated RCF	Enables wayside detection of impulsive damage	Affected by noise and threshold dependence
Optical-based methods	Profile geometry, rail displacement, FBG strain	Wheel flats, polygonal wear, hollow wear, and visible surface manifestations of RCF	Supports quantitative assessment and model calibration	Higher cost and calibration complexity

6. Prediction of Wheel Damage and Wear

Prediction studies in the reviewed literature do not cover all wheel damage modes to the same extent. The broad engineering objective is prediction of wheel damage, yet the most mature modelling work still focuses on wheel wear and profile evolution, whereas reliable prediction of wheel flats, rolling contact fatigue initiation, and mixed damage states remains less developed. The present section therefore retains wheel damage as the umbrella term for the overall review framework, while referring specifically to

wheel wear whenever the cited models are wear-centred. The distinction matters because it preserves terminological consistency without overstating the current maturity of prediction for all damage modes.

Current prediction studies fall into three broad categories: physics-based approaches, data-driven approaches, and hybrid approaches. The three categories differ in physical interpretability, data dependence, computational demand, robustness, and engineering applicability, and should therefore be compared on those terms rather than treated simply as alternative algorithmic options.

6.1 Physics-Based Approaches

Multi-body-dynamics-based prediction has been used widely in wheel–rail research. The typical workflow is outlined in Fig. 11. A vehicle–track coupled dynamics model is first built in mainstream simulation software to obtain wheel–rail interaction quantities such as contact force, creepage, and related variables. A local contact model is then used to resolve contact-patch behaviour and obtain more detailed contact parameters. Wear or RCF models are introduced to quantify material damage. Predicted material loss is mapped back to wheel–rail contact geometry through profile updating and smoothing, and the updated profile is then reintroduced into the dynamics model.

Iterative reanalysis allows long-term prediction of wheel profile evolution.

Recent research has refined each stage in order to improve both computational efficiency and physical realism. Model construction has become more scenario-specific, local contact modelling has moved from simple Hertzian assumptions towards simplified non-Hertzian formulations, and wear calculation has increasingly incorporated multi-physics effects and more realistic operating conditions. Even so, predictive performance still depends strongly on the balance among model fidelity, parameter availability, and computational cost. That trade-off remains one of the central issues in engineering deployment.

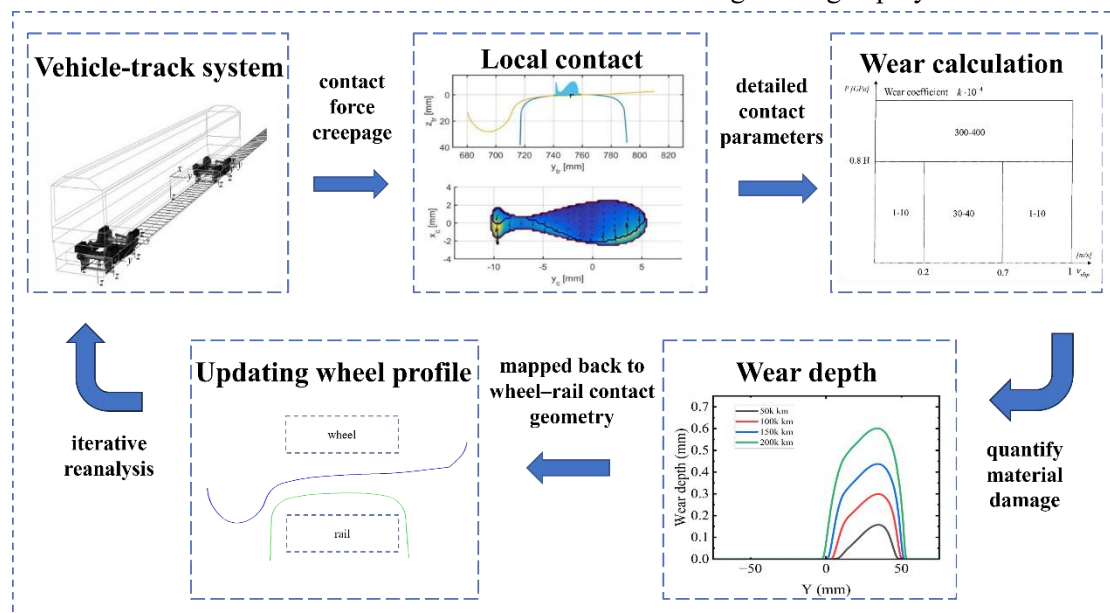


Fig. 11. General workflow for physics-based wheel-wear prediction.

6.1.1 Vehicle-Track Coupled Dynamics Models

In multi-body dynamics research, train mechanics models have progressed from simplified representations restricted to vertical-plane motion and idealised single operating conditions to spatial multi-body dynamics models with higher detail, wider coverage, and closer alignment with in-service scenarios. Model formulation has

also progressed from rigid multi-body dynamics to rigid-flexible coupled multi-body dynamics. Compared with rigid models, rigid-flexible coupled models can capture higher-frequency response and represent dynamic behaviour that is often underestimated when component flexibility is neglected.

Within the vehicle-track coupled dynamics framework, model development has

progressed along two complementary directions: greater system integration and explicit representation of real-world operating conditions. The first direction pursues higher system integration and finer resolution. Wu et al. [111] established a multi-train interaction model with an improved wheel–rail contact model and parallel computing, showing that traction and braking aggravate asymmetric wear and fatigue damage by altering wheel–rail contact state. In parallel, component flexibility has been introduced through rigid-flexible coupled models: Yang et al. [112] confirmed that polygonal wear markedly increases vibration of brake callipers and discs under high-speed and severe-wear conditions, and Wang et al. [113] demonstrated that brake block–wheel interaction produces a higher wear rate than pure wheel–rail contact.

The second direction recognises that real wheel-rail interaction is also governed by temperature, operating condition, and third-body media. Chen [114] incorporated temperature effects into a wheel-wear model through finite-element analysis, establishing that tread-braking temperature rise increases wear. Sang et al. [63] constructed a high-speed train model with gear transmission, finding that motor-car wear rate decreases with increasing speed due to traction-force variation, whereas trailer wear rate shows limited change. Braking-condition effects have been examined separately. Zhao et al.

[115] developed a train model incorporating a grinding block to investigate wear prediction under varying operating conditions. Kou et al. [116] compared motor-car and trailer wear in intercity trains, with both simulation and test results attributing more severe motor-car wear to traction and torsional effects. For defined operating scenarios, Bevan et al. [117] developed wear prediction models for electric and diesel multiple units to determine wheelset maintenance intervals. Collectively, these studies demonstrate that vehicle-track coupled dynamics models are most informative when operating conditions are represented explicitly rather than idealised, thereby providing the mechanistic foundation for the prediction approaches discussed in the following subsections.

6.1.2 Wheel–Rail Local Contact Models

Local contact modelling describes wheel–rail interaction at the contact patch, and the quality of that description has a direct effect on prediction accuracy. Early studies often adopted Hertzian contact with an elliptical-patch assumption. In practice, however, the contact patch is often non-elliptic, so a purely Hertzian treatment can introduce error into wear prediction. Non-Hertzian contact models were therefore developed to improve contact representation. Many of those models, however, remain computationally expensive and are difficult to apply in long-term iterative wear simulation.

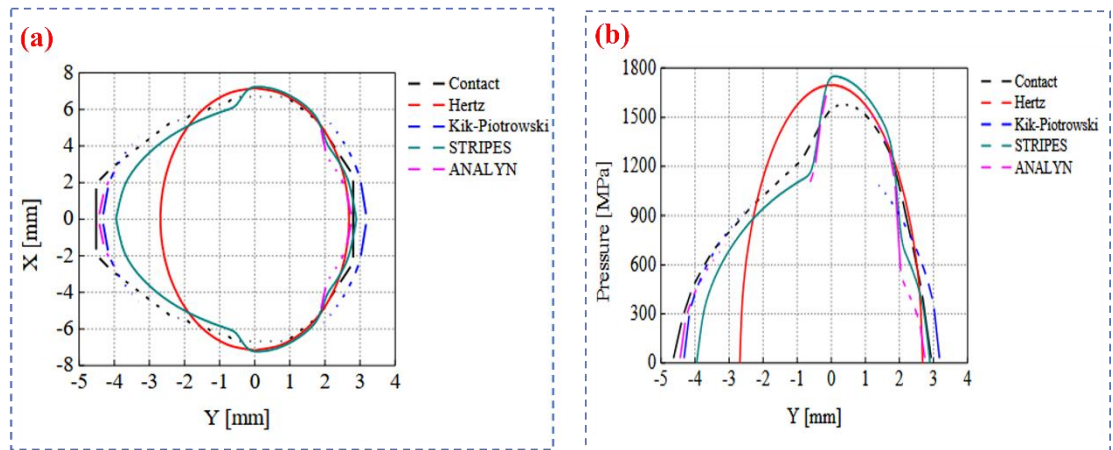


Fig. 12. Comparison of contact-patch shape and maximum pressure from KP, STRIPES, and ANALYN methods, Hertz theory, and the CONTACT program [119].

To balance contact fidelity and computational cost, several simplified non-Hertzian contact models have been proposed, including the Kik–Piotrowski method (KP) based on virtual penetration [118], the STRIPES method [119], and the ANALYN method [120]. All three can address non-Hertzian wheel–rail contact with useful

efficiency. The CONTACT numerical program is widely regarded as a high-accuracy reference for non-Hertzian wheel–rail contact analysis [121]. Fig. 12 compares contact solutions from KP, STRIPES, and ANALYN with Hertz theory and the CONTACT program [122].

Table 5. Main characteristics and limitations of representative wheel-rail contact models used in prediction.

Contact model	Fidelity	Computational cost	Representative application scenario	Main limitation
Hertz	Medium	Low	Long-term wear prediction, large-scale engineering simulation, elliptic contact	Elliptical-contact assumption is less accurate for worn, conformal, or two-point contact.
CONTACT	Very High	Very High	Benchmark validation for non-elliptic contact, high-precision contact patch analysis	High computational cost limits repeated long-term and fleet-scale simulations.
KP	High	Low	Non-elliptic contact wear simulation, integration with multi-body dynamics software	Virtual-penetration simplification may reduce fidelity when contact points change abruptly.
STRIPES	Medium	Medium	Non-elliptic contact handling in dynamic simulation	Simplified representation may reduce accuracy for strongly irregular contact and complex worn profiles.
ANALYN / ANALYN-yaw	High	Medium	Non-elliptic contact analysis considering wheelset yaw angle	Accuracy depends on appropriate treatment of complex profiles and wheelset yaw conditions.

MKP	High	Medium	Conformal / two-point contact scenarios with worn profiles	Requires calibration and validation for different worn profiles and complex contact states.

Yang et al. [123] developed a wheel-wear and fatigue-damage prediction model based on a non-Hertzian contact approach, which provides a more accurate description of wheel-rail contact and improves prediction of wheel wear and fatigue damage compared with a Hertzian algorithm. Existing non-Hertzian wear studies rarely include wheelset yaw effects. To address that limitation, Ye et al. [124] proposed a non-Hertzian normal contact model with wheelset yaw based on ANALYN and Sun’s approximate expression, referred to as ANALYN-yaw. Integration with the USFD wheel-wear prediction model improved prediction accuracy. Wang et al. [125] implemented the KP method for wheel–rail contact calculation in the multi-body dynamics software UM and obtained contact-stress distribution and slip distance within the contact patch. Output from contact analysis was then used as input to a wheel-tread wear prediction model in order to calculate wear distribution across the contact patch. Zhai et al. [126] addressed limitations of the traditional KP method for worn wheel and rail profiles by proposing an improved anti-interference non-Hertzian contact method, denoted as MKP. MKP removes normal-force jumps caused by abrupt contact-point change under worn conditions and improves contact calculation accuracy for conformal contact and two-point contact. Niu et al. [127] carried out long-distance EMU wear simulations using Hertzian and STRIPES contact algorithms. Similar wear amount and wear distribution were obtained in the early stages, whereas STRIPES produced results closer to in-service behaviour as simulation distance increased.

As wheel-rail contact research has advanced,

Hertzian contact alone has become increasingly insufficient for complex worn profiles, whereas the CONTACT program, despite high accuracy, remains computationally demanding. Simplified non-Hertzian models such as KP, STRIPES, ANALYN, ANALYN-yaw, and MKP were therefore developed to balance fidelity and efficiency. Suitable application range, relative accuracy, computational burden, and modelling limitations differ among these models. Table 5 therefore summarises their main characteristics and limitations to support informed model selection.

6.1.3 Wear Calculation Models

Wear calculation models used in wheel–rail research [128] mainly include Archard-type models based on normal load and sliding distance, USFD-type models based on frictional work or wear index, and frictional-work-based formulations developed at contact-patch level. These three approaches share a common structure—quantifying material removal through contact-patch-level mechanical quantities—but differ in the specific physical variable used to drive the wear calculation. In Archard-type modelling [129], the wear coefficient is commonly divided into several regions according to sliding velocity and contact pressure, and the coefficient values require calibration against experimental evidence.

In the Archard model, wear volume is proportional to the product of normal force and sliding distance and inversely proportional to material hardness. Eq. (2) is expressed as follows:

$$v = k \frac{Fs}{H} \quad (2)$$

where $v(m^3)$ represents the wear volume; k denotes the wear coefficient, which is determined by the sliding velocity and contact pressure at the contact point; H represents the material hardness; F represents the wheel-rail normal force; s (m) represents the sliding distance. Jendel [130] implemented the Archard wear model by discretising the contact patch into computational elements and evaluating wear depth at the centre of each element, as given in Eq. (3). In that formulation, p denotes the normal pressure density on each computational element.

$$\Delta z(x, y) = k \frac{ps}{H} \quad (3)$$

Within the Archard framework, the wear coefficient is usually defined as a function of element normal pressure and slip velocity, as

illustrated in Fig. 13(a). Slip velocity below 0.2 m/s or above 0.7 m/s corresponds to mild wear, whereas slip velocity between 0.2 m/s and 0.7 m/s corresponds to severe wear. When contact stress exceeds $0.8H$, where H denotes material hardness, the contact condition enters the catastrophic wear region. In numerical simulation of wheel-rail wear, the Archard wear model remains one of the basic tools for predicting material removal. Johansson and Andersson [24] coupled Kalker's FASTSIM algorithm with the Archard model to develop a three-dimensional dynamic framework for predicting long-term polygonal wear evolution in metro wheels; Du et al. [131] integrated the CONTACT program and the Archard model within a vehicle-track coupled dynamics framework to analyse the effects of material hardness and track condition on wear depth and profile evolution.

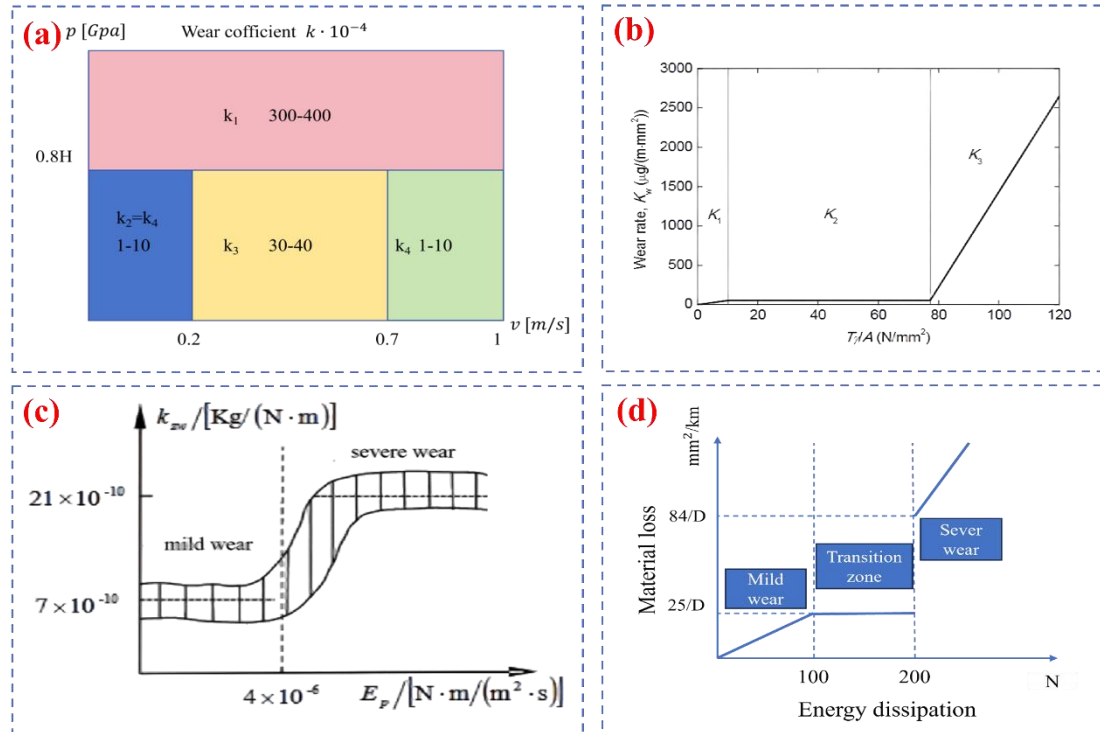


Fig. 13. Representative wear calculation models: (a) Archard model [130]; (b) USFD model [135]; (c) Zobory model [140]; (d) Pearce model [143].

To improve model fidelity, He et al. [132] developed a three-dimensional thermo-

mechanical coupled finite-element model incorporating initial defect, thermal effect,

and structural dynamics, showing that wheel–rail impact can generate high contact temperature and thermal softening which increase contact stress and wear depth. Xie et al. [133] introduced a modification participation coefficient into the Archard formulation to account for tread-modification-device effects, and Qi et al. [134] applied the Jendel model with field validation to analyse the influence of wheelset hunting motion on wear under varying excitation and track conditions. The Archard model therefore remains one of the main tools for simulating wheel–rail contact wear. Coupling with multi-physics fields and more realistic operating conditions has improved both prediction accuracy and engineering relevance.

While the Archard model relies on normal load as the primary wear driver, the USFD model [135] approaches wear from the perspective of energy dissipation within the contact patch, defining three wear regimes—mild, severe, and catastrophic—corresponding to coefficients K1, K2, and K3 in Fig. 13(b). The analytical expression for the wear rate K_W , representing the weight of material lost per rolling distance per contact area, is given by Eq. (4):

$$K_W = \begin{cases} 5.3I_W, I_W < 10.4 \\ 55.0, 10.4 < I_W < 77.2 \\ 61.9I_W - 4778.7, I_W > 77.2 \end{cases} \quad (4)$$

where I_W (N/mm^2) defined as local frictional power within the contact patch and can be evaluated using the wear index, as given in Eq. (5):

$$I_W(x, y) = \tau(x, y)\xi(x, y) \quad (5)$$

Where $\tau(x, y)$ (N/mm^2) and $\xi(x, y)$ denote tangential stress and creepage at contact patch mesh node (x, y) , respectively.

The wear of each contact patch is $\delta_{p(t)}(x, y)$ (mm)

$$\delta_{p(t)}(x, y) = \frac{K_W}{\rho} \Delta x \quad (6)$$

where ρ (Kg/m^3) is the density of the wheel material, and Δx (mm) is the width of meshes of the contact patch in rolling direction.

The wear contributions over the contact patch are then summed in the longitudinal direction. The wear distribution at a given cross-section is obtained from Eq. (7):

$$\delta_{p(t)}^{tot}(y) = \int_{-a(y)}^{+a(y)} \delta_{p(t)}(x, y) dx \quad (7)$$

Finally, the wear distribution over the full dynamic-simulation interval is accumulated as Eq. (8).

$$W_d(y) = \frac{1}{2\pi R} \int_{T_{start}}^{T_{end}} \delta_{p(t)}^{tot}(y) v dt \quad (8)$$

where R (m) is the nominal rolling radius, v (m/s) is vehicle speed, and T_{start} and T_{end} are the start and end times of the simulation, respectively.

The USFD model has been extensively coupled with different contact algorithms to build high-fidelity wear-prediction models. Ye et al. [124] combined a non-Hertzian contact model with the FaStrip tangential algorithm and the USFD wear function to incorporate bogie yaw angle effects. Ye et al. [23] further applied the USFD wear function in a flexible wheel–rail dynamics model to study the effects of wheel flats and operating speed on polygonal wear. The influence of system flexibility has been examined through several studies: Yang et al. [136] compared

different flexibility representations on long-term polygonal wear evolution, Tao et al. [137] found that a flexible track model predicts lower wear than a rigid-track model, and Li et al. [138] showed that asymmetric polygonal wear on both sides of a wheelset converges towards a high-order-dominated pattern. Beyond wear prediction, USFD-based modelling has also supported evaluation of operating strategies and profile design. Shatunov et al. [139] demonstrated that lateral load offset increases the USFD wear coefficient in small-radius curves, extending the model's utility to operating strategy evaluation.

Coupling non-Hertzian contact theory with system dynamics has therefore made the USFD model an important tool for simulating wheel-rail wear evolution, with clear value for maintenance strategy development and wheel-rail design optimisation.

An alternative route for wheel-damage prediction is based on frictional work. Wear in contacting bodies is accompanied by energy dissipation, and wear within the contact patch is often related to the total dissipated energy over that patch. Wear power in the wheel-rail contact patch can be defined as the product of tangential contact force and slip velocity. Zobory [140] proposed a wear-hypothesis model based on dissipated energy. The model assumes zero wear in the adhesion region of the contact patch, with wear confined to the slip region. Dissipated power at a point in the slip region is expressed by Eq. (9):

$$E_p(x, y, t) = p_x(x, y, t)v_x(x, y, t) + p_y(x, y, t)v_y(x, y, t) \quad (9)$$

where $E_p(x, y, t)$ ($N \cdot m / (m^2 \cdot s)$) Energy dissipation rate at a computational point within the contact patch; $P_k(x, y, t)$ (N / m^2) Tangential stress in the k-

direction at a computational point within the contact patch; $v_k(x, y, t)$ (m/s) Relative slip velocity in the k-direction at a computational point within the contact patch; Mass wear rate of material per unit time is introduced into the dissipated energy wear hypothesis model.

$$m_p(x, y, t) = k_{zw}E_p(x, y, t) \quad (10)$$

The mass wear rate per unit time is then introduced through Eq. (10). In that formulation, the wear coefficient relates to both material properties and dissipated energy, as determined by Zobory [140] through the relation illustrated in Fig. 13(c). This approach has been further refined by Wang et al. [141], who proposed a three-dimensional finite-element-based method defining frictional work as contact friction force multiplied by relative displacement, predicting the most severe wear near the nominal rolling circle with an expanding wear band as mileage increases. Ma et al. [142] introduced von Mises stress distribution into the framework and proposed an elastic-plastic partition method, where the frictional-work formulation accounts for material yield and frictional excitation in the plastic region. To avoid the computational burden of partitioning adhesion and slip zones inherent in the Zobory model, the Pearce model [143] offers an engineering simplification by replacing local energy integration with a macroscopic dissipated-energy metric, correlating wheel material loss through experimentally calibrated piecewise linear functions (Fig. 13(d)), with wear classified into mild, transition, and severe regions.

In summary, the Archard model, the USFD model, and frictional-work-based models form the core methodological basis of current wheel-rail wear prediction. Across these models, wear evolution is quantified through

variables such as wear depth, wear rate, contact pressure, sliding distance, wear coefficient, and frictional work. When considered together with crack depth and spalling-related RCF severity, these variables provide a quantitative basis for comparing material removal, profile evolution, and fatigue damage. Their continued development through multi-physics coupling, more realistic operating conditions, closer integration with non-Hertzian contact theory and system dynamics, and improved calibration against experimental and field evidence has progressively strengthened prediction accuracy and engineering applicability. Nevertheless, predictive performance remains sensitive to wear-coefficient calibration and contact-model fidelity, while the computational demands of iterative non-Hertzian analyses remain a barrier to fleet-level deployment. These limitations motivate the complementary use of data-driven approaches, which are examined in the following section.

6.2 Data-Driven Approaches

As multi-body dynamics methods have matured and sensing deployment has expanded, the limitations of purely physics-based approaches have become more apparent in data-rich operating environments. Data-driven approaches have therefore attracted increasing attention [144], especially for diagnosis, trend recognition, and short- to medium-term prediction. The main strengths of such approaches lie in pattern extraction and computational efficiency after training, whereas the main limitations remain tied to data quality, label availability, drift, and transferability across lines, vehicles, and operating conditions.

From the perspective of the present review, data-driven approaches for railway wheel-wear management face three persistent challenges that limit practical deployment

and long-term reliability. Fig. 14 therefore organises the literature around three core issues: label scarcity, cross-domain generalisation, and online updating with drift handling. The following subsections group the literature by engineering challenge rather than by algorithm name alone.

6.2.1 Mitigating Label Scarcity

Supervised learning methods, including deep neural networks (DNN), convolutional neural networks (CNN), and long short-term memory networks (LSTM), have achieved promising results in wheel-tread wear identification, flat classification, and wear-volume prediction. Their performance, however, depends heavily on the availability of large, high-quality labelled datasets. In rail transit, obtaining sufficient labelled fault samples is costly and often impractical. Research has therefore moved increasingly towards unsupervised and semi-supervised learning.

Unsupervised learning identifies structure in unlabelled data and thereby supports anomaly detection and cluster analysis without prior labels. Ni and Zhang [145] constructed wheel-health models from track-strain response features, enabling quantitative wear-level identification without defect samples. Magalhães et al. [146] employed sparse autoencoders on simulated track-acceleration data, while Guedes et al. [147] applied principal component analysis (PCA) to suppress environmental interference and enhance polygonal wear detection. Mohammadi et al. [148] used autoregressive models to extract stable features from acceleration signals for unsupervised wheel-flat detection. Most of those approaches construct a reference model for healthy operation and then detect anomalies through deviation from that baseline.

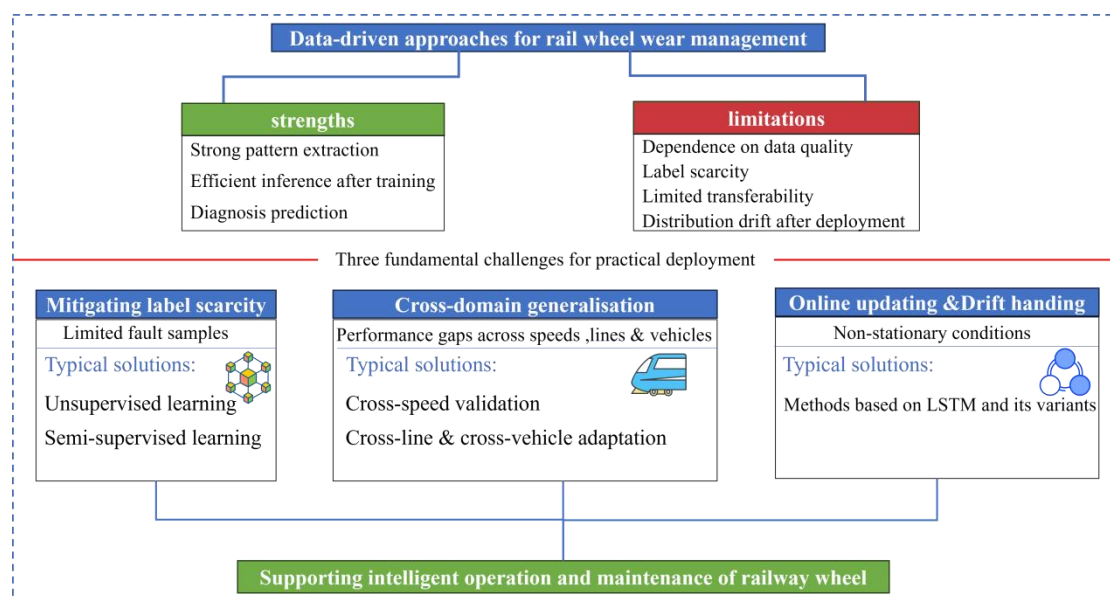


Fig. 14. Three main challenges for data-driven approaches.

Semi-supervised learning combines a small labelled set with a larger volume of unlabelled data, improving monitoring efficiency while reducing annotation cost. Shim et al. [149] applied an improved LeNet-5 within a Deep SVDD framework, achieving 94% classification accuracy using only normal data for training. Ozdemir and Koc [150] proposed a teacher–student network based on YOLOv4 with pseudo-labelling to expand the training set iteratively, and Wang et al. [151] combined distributed fibre-optic acoustic sensing with semi-supervised deep learning, achieving 97.91% accuracy for high-speed rail track inspection. These results demonstrate that semi-supervised learning can substantially reduce dependence on large labelled datasets while retaining useful diagnostic capability.

6.2.2 Cross-Domain Generalisation

Models trained under specific operating conditions often suffer performance degradation when applied to different speeds, line geometries, or vehicle types. Validation across speed, line, and vehicle type is therefore essential for practical deployment.

To improve cross-speed generalisation, Ye et al. [152] proposed a method combining activated time-domain images (ATDI) with a two-dimensional CNN. By introducing an adaptive activation function and cyclic shift operation, the model maintained high accuracy across multiple speed levels. Comparative experiments with a short-time Fourier transform (STFT)-based method demonstrated stronger cross-speed generalisation and better anti-interference capability for the ATDI-DNN model. Wang et al. [153] employed an identity-based multi-layer extreme learning machine (I-MLELM) and its derived variant (DELM) for wear prediction under multiple operating conditions, incorporating speed, mileage, and curve radius as inputs. Quantum-behaved particle swarm optimisation (QPSO) [154] was used for parameter tuning, enabling prediction across diverse operational scenarios. Shebani and Iwnicki [88] applied a nonlinear autoregressive network with exogenous inputs using load and speed as predictors, and validated its performance under varying loads and speeds through experiments.

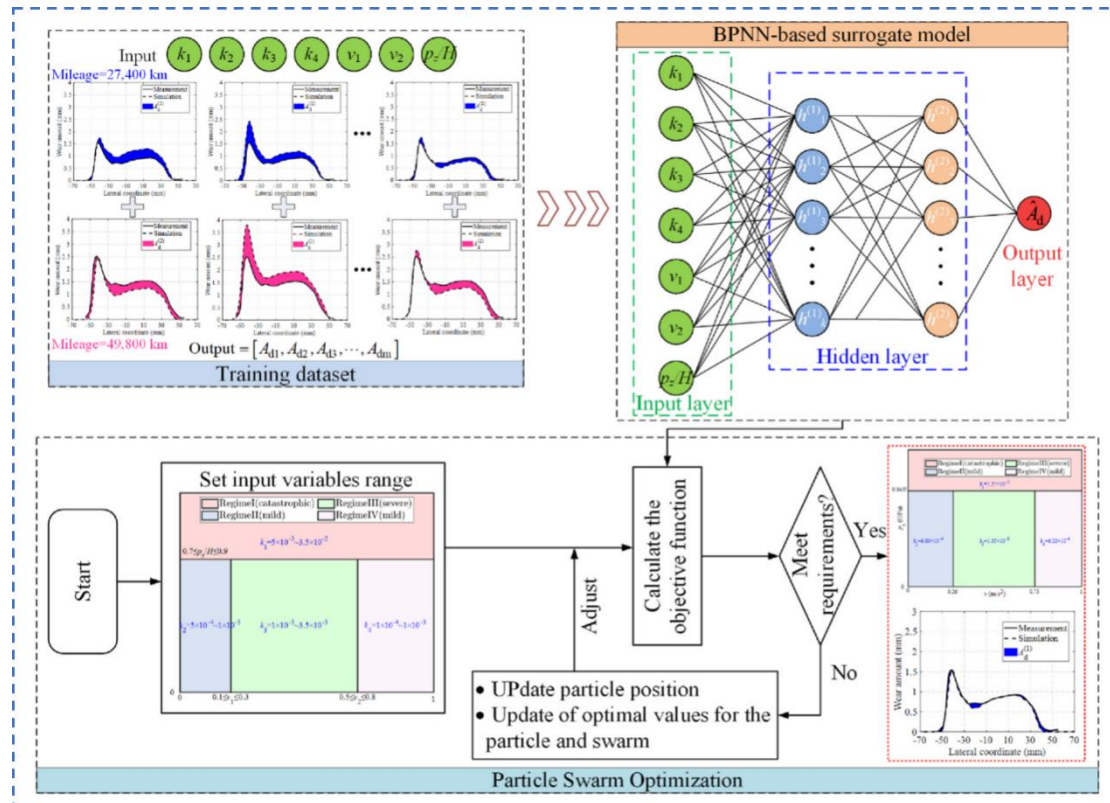


Fig. 15. Adjustment strategy for improved generalisation based on BPNN-PSO [155].

Cross-line and cross-vehicle validation are equally important. Wen et al. [155] combined a back-propagation neural network (BPNN) with particle swarm optimisation (PSO) to develop a long-term wheel-wear prediction model that includes the effect of frictional temperature rise. Through thermo-mechanical coupling and adaptive adjustment of the Archard wear law, as shown in Fig. 15, the results indicated that high temperature can accelerate wear during curve negotiation. Ye et al. [124] later introduced a Kriging surrogate model with a PSO-based automatic calibration strategy to optimise wear coefficients in the USFD model, which improved prediction of wear distribution across varying line conditions. The available studies therefore show that model evaluation across different speeds, line types, and vehicle configurations is necessary if genuine transferability is to be established.

6.2.3 Online Updating and Drift Handling

Wheel wear is a slowly varying process influenced by non-stationary factors such as ambient temperature and wheel-rail interface conditions. Those factors can cause concept drift after model deployment and therefore create a clear need for online updating and real-time anomaly monitoring.

Methods based on LSTM and related variants have shown promise in temporal feature extraction and online monitoring. Huang et al. [156] achieved 96.6% accuracy for real-time bogie fault classification by extracting spatio-temporal features from raw vibration signals. Zhang et al. [157] applied LSTM to classify voltage signals from a self-powered intelligent suspension system for continuous running-state recognition, and Liu et al. [158] proposed an LSTM-based model for axle-temperature anomaly detection under high-noise conditions. Such approaches adapt to

new data distributions through incremental learning.

Dynamic adjustment strategies have also been developed to cope with environmental variation. Gao et al. [159], for example, combined a genetic algorithm with a wavelet neural network to adjust flat-assessment models online on the basis of wheel-rail noise. Wang et al. [160] proposed a multi-layer wavelet-integrated convolutional network with a dynamic frequency-aggregation strategy to focus on key frequency bands, thereby improving wear-prediction accuracy based on real-time vibration and speed inputs and supporting operation and maintenance decisions. The unsupervised health models proposed by Ni and Zhang [145] and Magalhães et al. [146] can also serve as drift-monitoring tools by triggering alarms when measured signals depart from the healthy baseline. Guedes et al. [147] improved the robustness of wheel polygonal wear identification by using PCA to suppress environmental interference. The available studies therefore show that online updating is essential if data-driven models are to remain reliable under changing service conditions.

A common reason behind label scarcity, weak transferability, and online drift is that measured monitoring data rarely correspond to a single defect under service conditions. Force, vibration, acoustic, strain, or fibre-optic signals may simultaneously contain wheel-flat impacts, polygonal-order components, track irregularity, speed variation, environmental interference, and sensor noise. Under label scarcity, unsupervised health modelling and PCA-based interference suppression can help extract defect-related deviations without complete defect labels [145,147]. For cross-domain generalisation, activated time-domain images combined with CNNs can enhance shock-response features and

improve wheel-defect detection across different speeds [152]. For online updating and drift handling, wavelet-integrated CNNs with dynamic frequency aggregation can focus on key frequency bands from real-time vibration and speed inputs, thereby improving wear prediction under changing operating conditions [160]. These methods can reduce label dependence and produce more stable defect-related features. Their physical interpretation, however, still requires comparison with measured wheel condition, profile inspection, and maintenance records.

The evidence reviewed in this section supports the feasibility of mixed-signal feature extraction, but does not yet establish its robustness in service. Most representative studies have been evaluated using simulated signals, controlled laboratory or bench tests, or restricted datasets. These conditions are useful for developing and comparing methods, but they cannot reproduce the full variability of railway operation, where environmental noise, overlapping responses from several sources, sensor drift, changing wheel-rail contact conditions, and sparse damage labels may affect the extracted features. Their transfer to maintenance practice should therefore be examined using longitudinal field data from different vehicles, lines, and operating conditions, with the extracted features and corresponding wheel condition checked against independent wheel inspections and maintenance records. Such validation would clarify whether improvements observed under controlled conditions remain stable enough to support diagnosis and damage-evolution prediction in service.

These challenges show why purely data-driven models are insufficient for operational decision-making. Their performance remains bounded by training-data representativeness

and weak extrapolation outside the observed domain. Practical remedies include domain adaptation, transfer learning, semi-supervised learning, physics-informed learning, and fleet-level data fusion, which can reduce label dependence and improve robustness across vehicles, lines, and operating environments. This complementarity motivates hybrid modelling, in which physical knowledge supports extrapolation and data-driven components provide adaptation to service conditions.

6.3 Hybrid Approaches

Hybrid approaches aim to combine the interpretability of physics-based modelling with the adaptability of data-driven analysis. In this review, hybrid modelling refers to the explicit coupling among mechanism-based models, monitoring data, and computational learning for diagnosis, prediction, or maintenance support. Methodologically, hybrid modelling usually involves three functions: physical guidance of data interpretation or learning, data-driven updating or acceleration of mechanism-based prediction, and decision-oriented use of prediction outputs. As shown in Fig. 16, these functions are organised into a feedback-enabled pathway involving perception, prediction, and decision. Their value lies in improving interpretability, robustness, and engineering usefulness.

6.3.1 Perception and Parameter Calibration

At the perception stage, monitoring data are used for parameter inversion, calibration, and wheel wear level identification. Sun et al. [161] developed an on-board polygonal-wear detection method using axle-box vibration acceleration, while Chen et al. [162] proposed adaptive chirp mode decomposition for quantitative polygonal-wear detection under non-stationary

conditions. These studies show that monitoring features become more useful when interpreted together with wheel-rail dynamics and damage mechanisms.

Physics-informed learning, including Physics-Informed Neural Networks (PINNs), extends this guidance function by embedding governing equations, contact constraints, boundary conditions, and wear- or RCF-related prior knowledge into model training [163-164]. In the literature reviewed here, the main applications concern parameter identification and the computationally efficient approximation of physics-based solutions. Mo et al. [165], for example, combined a physics-informed Laplace neural operator with a multiscale CNN to identify vertical wheel-rail forces from bridge displacement responses. This study addresses inverse identification of wheel-rail forces rather than direct long-term prediction of wheel damage. Direct applications of PINNs to long-term wheel wear or RCF evolution remain scarce. The reviewed studies do not yet establish reliable prediction under changing service conditions, and a field-validated PINN system for operational wheel-damage prediction was not identified within the scope of this review. PINNs are therefore treated here as an emerging component of hybrid modelling, with potential for further development rather than as an established operational method. Further progress requires realistic contact and material descriptions, longitudinal monitoring data, uncertainty assessment, and staged validation from controlled tests to independent field data.

6.3.2 Prediction and Model Updating

After the wheel wear level has been identified, hybrid prediction uses surrogate-model order reduction and data-driven updating to obtain wear performance

prediction. Zhou et al. [166] combined wheel-profile optimisation with wear prediction through parametric profile representation, multi-objective optimisation, and surrogate modelling. Gopan et al. [167] integrated an artificial neural network with a genetic algorithm for prediction and optimisation. These studies show that hybrid updating can reduce computational cost and improve adaptability, although its reliability still depends on the physical basis of the contact model, wear law, and calibration data.

6.3.3 Decision and Feedback

At the decision stage, prediction outputs are linked with mechanism-constrained learning, control strategy optimisation, and feedback adjustment. Xu et al. [168] introduced probabilistic treatment through vehicle-track dynamics and probability density evolution, while Ai et al. [169] used iterative learning control to improve dynamic performance. For wheel damage prediction, this stage should connect wear state, profile evolution, polygonal order, wheel-flat severity, or RCF

risk with inspection, re-profiling, speed management, and maintenance planning. Feedback from monitoring and maintenance records can then be used to update model parameters, strategy constraints, and decision thresholds.

Taken together, Fig. 16 links Monitoring Data with Parameter Inversion Calibration and Wheel Wear Level in the perception stage, Surrogate Model Order Reduction and Wear Performance Prediction in the prediction stage, and Mechanism-Constrained Learning, Control Strategy Optimisation, and Feedback Adjustment in the decision stage. Prior Knowledge, Model Guidance, and Strategy Constraints provide cross-stage guidance. However, most existing studies remain task-specific, and a fully validated monitoring-prediction-maintenance loop is still insufficiently developed. Fig. 16 should therefore be understood as a conceptual integration pathway rather than a validated operational workflow.

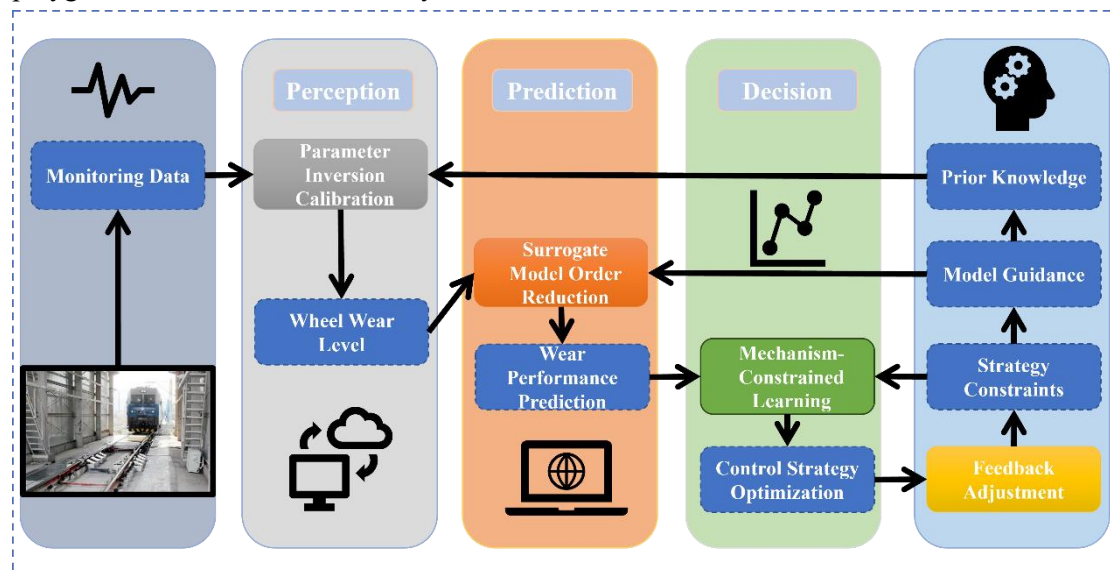


Fig. 16. Conceptual hybrid framework linking monitoring, prediction, and maintenance decision-making for wheel damage.

Table 6. Comparison of representative prediction approaches for wheel damage and wear.

Dimension	Physics-based approaches	Data-driven	Hybrid approaches
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approaches			
Prediction performance	Suitable for long-term profile and wear trends; sensitive to wear-coefficient calibration and contact-model fidelity	Effective within represented operating conditions; limited for continuous wear regression and extrapolation	Potentially improves consistency through physical constraints and data updating; long-term field evidence limited
Computational cost	High; iterative multi-body dynamics simulation with non-Hertzian contact requires days per scenario	Low after training; suitable for real-time applications	Medium; surrogate models reduce physics cost; training adds overhead
Data dependence	Low to moderate; requires material parameters and contact coefficients from experiments	High; requires large, high-quality labelled datasets spanning diverse conditions	Moderate; physics generates synthetic data to alleviate label scarcity
Cross-domain generalisation	Moderate; governed by physical laws but sensitive to scenario-specific calibration	Weak; performance degrades markedly across different lines, speeds, or vehicle types	Strong; physics provides extrapolation capacity, data adapts to context
Engineering interpretability	High; mechanisms are explicit and traceable to physical causes	Low; black-box nature limits trust in safety-critical decisions	Medium to high; physical structure constrains outputs, improving transparency
Uncertainty handling	Can propagate parameter and scenario uncertainty, but repeated simulation is costly	Often implicit; calibrated ensembles or Bayesian methods are needed	Can combine model and data uncertainty, but field validation remains limited
Maintenance applicability	Provides traceable wear, profile, and RCF indicators for inspection or re-profiling	Supports alarms and trend prediction, but thresholds require field calibration	Offers the strongest potential for standards-informed thresholds and feedback, but is not yet fully operationally validated

The reviewed evidence indicates that physics-based, data-driven, and hybrid approaches are complementary rather than competing paradigms [170]. Physics-based approaches provide mechanistic

interpretability, data-driven approaches provide efficiency and adaptability under rich sensing conditions, and hybrid approaches offer the strongest potential for linking diagnosis, prediction, uncertainty

handling, and maintenance decision-making. Table 6 summarises their main differences in prediction performance, data dependence, computational cost, cross-domain transferability, engineering interpretability, uncertainty handling, and maintenance applicability.

From an engineering perspective, model prediction outputs should be interpreted together with current maintenance and inspection criteria. Physics-based approaches can provide characteristic indicators such as wear depth and RCF risk, while data-driven approaches support efficient fault diagnosis and damage-trend prediction. Hybrid approaches further combine physical priors, monitoring data, and maintenance feedback, and therefore provide a bridge between prediction outputs and maintenance standards. However, the outputs of all three approaches still need to be evaluated against applicable industry criteria. For example, EN 15313:2024 and GTJ 0044-2025 provide references for wheelset maintenance and inspection, while ISO 55000:2024 provides a life-cycle asset-management framework. By comparing predicted damage indicators with these criteria, model outputs can support maintenance actions such as non-destructive inspection, tread re-profiling, wheel replacement, inspection interval adjustment, and maintenance-priority ranking. Maintenance histories and field monitoring records can then feed back into model calibration and warning-threshold optimisation. Therefore, hybrid modelling represents a promising technical route for building a closed loop among condition monitoring, damage prediction, and maintenance decision-making.

7. Summary, Research Gaps, and Future Directions

7.1 Main Conclusions

Wheel damage remains a persistent engineering challenge because it changes wheel-rail contact conditions, affects vehicle-track dynamics, and directly influences safety, maintenance cost, and component life. The reviewed literature shows substantial progress in mechanism interpretation, factor analysis, monitoring, and prediction, but these strands remain more mature individually than as parts of an integrated maintenance framework.

(1) The principal wheel damage modes include polygonal wear, wheel flats, rolling contact fatigue, and hollow wear. Initiation and growth arise from different but interacting mechanisms, including structural resonance, frictional instability, local defect feedback, and coupled wear–fatigue evolution. No single mechanism accounts for all reported cases across different vehicle types and operating environments.

(2) Wheel damage evolution is governed jointly by wheel–rail hardness matching, material properties, operating conditions, and environmental or interfacial conditions. The literature provides useful quantitative guidance for some parameters, but the effect of any single factor cannot be interpreted reliably without considering coupling with contact geometry, creepage, friction, thermal state, and material response.

(3) Monitoring and diagnosis draw on two broad evidence sources: controlled bench testing and in-service sensing. Bench testing supports mechanism verification, parameter calibration, and model development under

repeatable conditions, whereas in-service monitoring captures operational variability and damage progression under real railway environments. Force- and vibration-based, acoustic-based, and optical-based methods each offer distinct strengths and limitations.

(4) Prediction studies can be grouped into physics-based, data-driven, and hybrid approaches. Prediction maturity, however, remains uneven across damage modes. The strongest modelling progress has been made for wheel wear and profile evolution, whereas prediction of other damage modes remains less developed. Further progress depends not only on more advanced algorithms, but also on stronger links among mechanism understanding, monitoring evidence, uncertainty assessment, and maintenance criteria.

To support these conclusions and respond to the need for a clearer synthesis of the reviewed evidence, Appendix Table A1 provides a standardised extraction of representative studies across the full-chain structure of this review. The table summarises key studies in terms of damage mode or thematic category, method, main findings, limitations, and relevance to mechanism interpretation, monitoring evidence, prediction, or maintenance application, together with the qualitative evidence-strength annotation. It therefore complements the narrative discussion by making the evidence base more transparent and by allowing readers to compare representative studies across mechanisms, influencing factors, monitoring approaches, and prediction models.

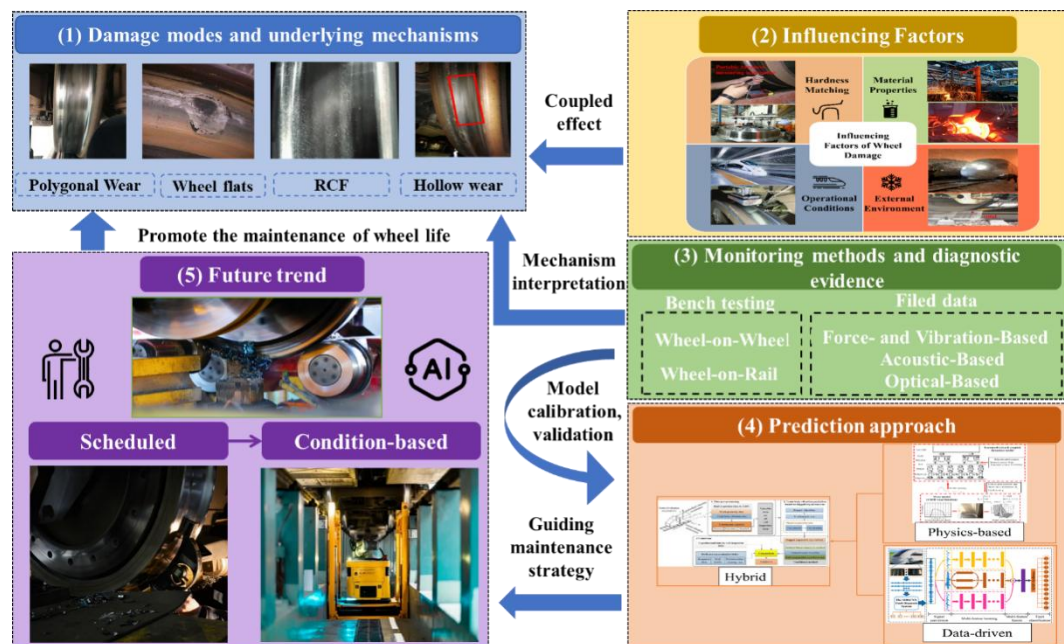


Fig. 17. Research framework and future pathway for railway wheel damage management from scheduled to condition-based maintenance.

7.2 Research Gaps and Future Directions

Fig. 17 summarises the research pathway from mechanism interpretation and condition monitoring towards prediction-enabled condition-based maintenance. The main

challenge is to convert fragmented advances into an operational framework that integrates mechanisms, sensing evidence, predictive capability, uncertainty assessment, and maintenance decision criteria. The following priorities should therefore be understood as a

staged roadmap rather than as independent tasks: benchmark data provide the evidence basis, calibrated sensing improves data reliability, transferable and adaptive models support prediction across operating conditions, uncertainty quantification improves confidence assessment, and maintenance-oriented interpretation closes the feedback loop.

(1) Benchmark datasets and evaluation frameworks should be established for wheel damage research. Such datasets should include standardised damage labels and severity grades, operating metadata such as speed, axle load, mileage, braking condition, curve radius, temperature, and line type, sensor information such as sensor type, installation position, sampling rate, and calibration record, as well as ground-truth data from wheel-profile measurement, ultrasonic inspection, lathe records, and maintenance reports. Predefined training, validation, and testing partitions across different lines and vehicles would allow models to be evaluated in terms of accuracy, transferability, robustness, uncertainty calibration, and maintenance usefulness

(2) Field-applicable sensor calibration strategies should be developed for complex operating conditions. To reduce measurement error in wayside and onboard sensors under demanding service conditions such as high-speed, heavy-haul, and low-temperature operation, dynamic calibration models are needed to improve data accuracy and reliability and to provide stronger support for diagnosis and prediction.

(3) Cross-line and cross-vehicle transfer evaluation should be strengthened for wheel-damage diagnosis and prediction models. Current models still show limited generalisation across lines, vehicle types, and

operating conditions. Transfer-learning frameworks and structured validation protocols are therefore needed to support rapid adaptation across multiple scenarios.

(4) Online updating and drift-monitoring mechanisms should be developed for wheel-wear prediction models. Because model performance can deteriorate as data distribution and damage mechanisms change during operation, real-time updating strategies are required to support long-term prediction reliability.

(5) Uncertainty quantification should be treated as a multisource issue involving prediction uncertainty, sensor uncertainty, domain-shift uncertainty, model-calibration uncertainty, and maintenance-threshold uncertainty. These uncertainties arise from limited data, model assumptions, parameter calibration, environmental noise, sensor drift, and transfer across different vehicles, lines, speeds, or climates. Future work should propagate uncertainty from sensing to prediction and maintenance decisions using sensitivity analysis, Bayesian updating, probabilistic prediction intervals, ensemble modelling, benchmark-based comparison, and online correction.

(6) Prediction outputs should be linked to maintenance decisions. For example, wheel-flat severity may inform re-profiling priority, RCF risk may trigger ultrasonic or other non-destructive inspection, polygonal order or amplitude may support resonance checking and speed-management assessment, and wear depth or flange-thickness loss may guide inspection-interval adjustment, re-profiling, or wheel replacement. These actions should be checked against applicable wheelset maintenance criteria and operator-specific maintenance plans rather than determined by model outputs alone.

Inspection and maintenance records can then feed back into model calibration and threshold refinement. Hybrid models may provide a stronger future pathway for this feedback process, although maintenance-oriented interpretation remains necessary for all prediction approaches.

Overall, future progress depends on turning monitoring, prediction, and maintenance into a technically explicit framework supported by benchmark data, interpretable models, reliable thresholds, and maintenance-relevant validation. Wheel damage research should therefore move beyond isolated improvements in diagnostic or predictive accuracy towards stronger links among mechanism understanding, sensing evidence, predictive models, uncertainty assessment, and maintenance criteria. Digital twins, real-

time predictive maintenance, uncertainty-aware AI, and explainable AI provide complementary routes for this integration. A digital-twin framework can continuously update wheel condition by combining vehicle-track dynamics, wheel-profile measurements, wayside and onboard sensing, and maintenance records. Uncertainty-aware and explainable AI can then quantify confidence, identify the monitoring features, operating conditions, and physical variables that drive model outputs, and support maintenance actions such as inspection, re-profiling, speed restriction, or wheel replacement. Such integration would support a shift from periodic inspection towards evidence-based predictive maintenance while retaining physical interpretability and traceable decision criteria.

CRediT authorship contribution statement

Tengchi Sun: Writing – original draft, Visualization, Conceptualization. **Ruichen Wang:** Writing – original draft, Supervision, Funding acquisition. **Haotian Lyu:** Writing – review & editing, Visualization, Funding acquisition, Data curation. **Jiale Zhang:** Visualization, Methodology, Investigation, Conceptualization. **Zifei He:** Writing – original draft, Visualization, Validation, Software.

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Data availability

Data will be made available on request.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

Appendix Table A1

Standardised extraction of representative studies across thematic categories.

The table summarises representative studies selected from the reviewed literature and aligns them with the full-chain structure of this review: damage mechanisms, influencing factors, monitoring evidence, and prediction approaches.

Thematic category	Subcategory	Reference	Method	Key findings	Limitations	Relevance to this review	Evidence strength
Damage mechanisms	Polygonal wear	Tao et al. (2020) [2]	Critical literature review	Identified three main mechanism families: resonance-driven excitation, friction-induced self-excited vibration, and initial-defect-triggered feedback; no universal mechanism explains all cases.	Review-based synthesis; limited quantitative comparison among mechanisms.	Supports the mechanism classification used in Section 3.1 and explains why monitoring and prediction must be mechanism-informed.	Medium
	Polygonal wear	Jin et al. (2012) [7]	Field axle-box acceleration analysis and vehicle-track dynamics	Linked wheelset bending resonance to creep-force fluctuation and non-uniform wear accumulation.	Track flexibility and long-term wear validation were limited.	Supports the connection between polygonal wear mechanisms and high-frequency axle-box acceleration signals.	Medium
	Polygonal wear	Ye et al. (2020) [23]	Flexible wheel-rail dynamics and USFD wear model	Showed that wheel flats can trigger P2 resonance and initiate or aggravate polygonal wear.	Thermal effects, detailed flat geometry, and long-term field validation were not fully considered.	Links local tread defects to polygonal wear evolution and supports early flat detection as a preventive measure.	Medium
	Wheel flat	Bian et al. (2013) [29]	Three-dimensional finite element wheel-rail impact model	Wheel flats generate periodic impact force; response amplitude increases with flat length and speed.	No full experimental validation; simplified contact and material response.	Provides mechanical basis for force- and vibration-based flat detection and impact-related maintenance thresholds.	Low
	RCF	Zhou et al. (2015) [40]	JD-1 test rig, SEM observation, and	Lateral force promotes plastic deformation accumulation and accelerates crack	Small-scale specimens may not fully reproduce full-scale contact	Shows why RCF prediction should include lateral force, creepage, and	Medium

			hardness measurement	initiation and spalling on the wheel tread.	stress and service load spectra.	material response.	
Influencing factors	Subsurface RCF	Zeng et al. (2020) [42]	Microstructural observation, stress analysis, and fatigue testing	Macroscopic rim defects such as inclusions and voids can initiate subsurface RCF cracks.	Quantitative defect-life relationship remains insufficiently established.	Supports the need for defect-sensitive inspection and fatigue models with initial material defects.	Medium
	Hollow wear	Jiang et al. (2025) [43]	Field vibration tests and coupled dynamics simulation	Hollow wear changes equivalent conicity and can induce bogie hunting and reduced running stability.	Formation mechanism and quantitative wear-hunting thresholds remain insufficiently clarified.	Consistent with the article's view that hollow wear is profile-dependent and requires profile or vibration-based monitoring.	Medium
	Hardness matching	Chang et al. (2018) [52]	Amsler wear testing using different wheel-rail material pairings	Wheel-rail hardness ratio below 1.05 promotes polygonal wear, whereas ratios above 1.36 suppress its development; a range of 1.1-1.4 is often suggested.	Small-scale testing and limited material combinations restrict direct generalisation.	Provides quantitative material guidance and supports hardness-dependent wear coefficient calibration.	Medium
	Material properties	Chen et al. (2015) [58]	MMSA-2A wear testing and hardness measurement	Higher wheel carbon content and hardness reduce wheel wear but may aggravate rail spalling and internal fatigue crack growth.	Third-body media and complex service conditions were not fully represented.	Highlights the wheel-rail life trade-off and the need to consider wheel and rail damage together.	Medium
	Operating speed	He et al. (2016) [64]	Small-scale wheel-rail simulation test	Increasing speed can reduce wear rate but intensify RCF, showing a clear wear-RCF competition.	Limited speed range and simplified traction/braking conditions.	Supports speed-dependent maintenance priorities and motivates hybrid models for coupled wear-fatigue behaviour.	Medium
	Environmental conditions	Shen et al. (2022) [67]	Low-temperature wheel-rail test rig	Low temperature shifts wear from abrasive/oxidative behaviour towards fatigue-dominated damage.	Temperature cycling, humidity interaction, and field thresholds remain insufficiently quantified.	Supports environment-specific monitoring and temperature-dependent prediction models.	Medium
	Bench testing	Braghin et al. (2006) [87]	Twin-disc tests and full-scale rig validation	Established a frictional-work-based wear model with three wear regimes and engineering-level prediction accuracy.	Wear coefficients are material-specific and require recalibration for other conditions.	Provides controlled evidence for wear coefficient calibration and physics-based prediction.	High
	Bench testing	Yamashita et al. (2022)	Scaled roller rig and wear-simulation-based	Integrated wear evolution into wheel-profile optimisation and reduced flange	Scaled contact conditions differ from full-scale service	Connects bench evidence, prediction, and re-profiling-	Medium

		[91]	profile optimisation	wear and tread damage.	conditions.	oriented maintenance design.	
	Force- and vibration-based methods	Liu and Zhai (2014) [93]	Vehicle-track coupled dynamics model	Polygonal wheels generate identifiable time- and frequency-domain wheel-rail force fluctuations.	Mainly vertical dynamics; field validation was limited.	Supports the use of force, strain, and vibration signals for polygonal wear diagnosis.	Low
	Acoustic-based methods	Komorski et al. (2018) [98]	Wayside microphone array and time-frequency analysis	Wheel flats generate periodic impact noise that can be detected using time-frequency methods.	Environmental noise and empirical detection thresholds affect robustness.	Supports low-cost wayside acoustic detection for wheel flats and maintenance triggering.	Medium
	Optical-based methods	Liu et al. (2019) [108]	Wayside FBG sensing and Bayesian blind source separation	FBG strain sensing can detect minor wheel defects and separate defect-induced strain responses.	Requires multi-sensor layout and relatively complex signal processing.	Provides high-quality strain evidence for early defect detection and online model updating.	Medium
	Physics-based approaches	Li et al. (2023) [138]	Rigid-flexible dynamics, KP contact model, and USFD wear model	Long-term polygonal wear simulation showed convergence towards high-order-dominated patterns and highlighted the role of wheelset flexibility.	Thermal and third-body effects were not fully included; computational cost is high.	Represents physics-based prediction of wear evolution and supports maintenance interval assessment.	Medium
Prediction approaches	Data-driven approaches	Ye et al. (2023) [152]	Activated time-domain image method and CNN using axle-box acceleration	The ATDI-CNN approach improves cross-speed wheel-flat detection compared with conventional STFT-based features.	Requires labelled data and mainly addresses classification rather than continuous wear regression.	Illustrates the value and limitations of data-driven diagnosis under variable-speed conditions.	Medium
	Hybrid approaches	Wen et al. (2025) [155]	BPNN, PSO, and temperature-corrected Archard wear law	Hybrid modelling accounts for thermo-mechanical effects and improves wheel-wear prediction compared with purely physics-based calibration.	Simplified thermal representation and limited long-term field validation.	Shows how data-driven calibration can update physics-based wear prediction and support maintenance decisions.	Medium

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