https://doi.org/10.37965/jdmd.2026.1233

Railway Wheel Life-Cycle Management: Design, Degradation, Monitoring, and Condition-Based Maintenance

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Received 28 February 2026 | Revised 07 April 2026 | Accepted 16 April 2026 | Posted Online 18 April 2026

Abstract: Increasing operating speed, axle load and utilisation intensify contact forces, creepages and excitation frequencies at the wheel-rail interface, making tread and flange degradation a persistent challenge in modern railway operation. Railway wheels are safety-critical load-bearing components, and service performance is governed by coupled evolution of wear, rolling contact fatigue (RCF), out-of-roundness and thermally influenced surface response under vehicle-track coupled dynamics. The review adopts a life-cycle structure covering design and manufacture, in-service degradation with prediction, and condition monitoring with maintenance intervention. For design and manufacture, the discussion covers wheel steel design and heat treatment, profile design and equivalent conicity control, process routes with residual stress management, and durability under regional environments. For in-service operation, wheel-rail system matching, wear and profile evolution modelling and RCF assessment are compared in terms of governing assumptions, required inputs and applicability across operating regimes. For condition-based maintenance, the review links depot inspection, wayside and on-board monitoring and decision rules to intervention options including turning, reprofiling, laser cladding repair and surface strengthening. The review highlights a closed-loop view of wheel life management in which prediction, monitoring and intervention are aligned against route-specific loading spectra, safety margin and whole-life cost.

Keywords: wheel life cycle; wheel service performance; wear prediction; condition monitoring; turning and reprofiling; maintenance intervention

1. Introduction and scope

The rapid expansion of railway networks, together with sustained increases in operating speed, axle load, and traffic density, has made the wheel-rail interface one of the

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most critical locations governing the safety, efficiency, and durability of modern railway systems. Under increasingly demanding service conditions, tread wear, flange wear, out of roundness, and rolling contact fatigue (RCF) remain persistent challenges in both high-density passenger transport and heavy haul freight operations. Such degradation arises from the combined action of wheel-rail contact mechanics, vehicle-track coupled dynamics, traction and braking loads, and environmental exposure, and can affect running stability, ride quality, braking performance, maintenance demand, and the service life of both vehicle and track components.

Although substantial research has been devoted to railway wheel performance, most published studies remain focused on individual topics in isolation, including wear mechanisms, RCF assessment, profile optimisation, condition monitoring, or repair technologies. Such a fragmented view is increasingly inadequate for modern railway applications, because wheel performance is inherently shaped by interactions across the full-service process. Material composition, manufacturing route, and initial geometry determine the starting condition of the wheel; operating conditions govern the evolution of contact state, damage accumulation, and near surface response; maintenance actions repeatedly modify profile geometry and material condition over successive service cycles. A comprehensive understanding of wheel performance therefore requires a life cycle perspective capable of linking design, manufacture, operation, degradation, monitoring, and intervention within a unified technical framework.

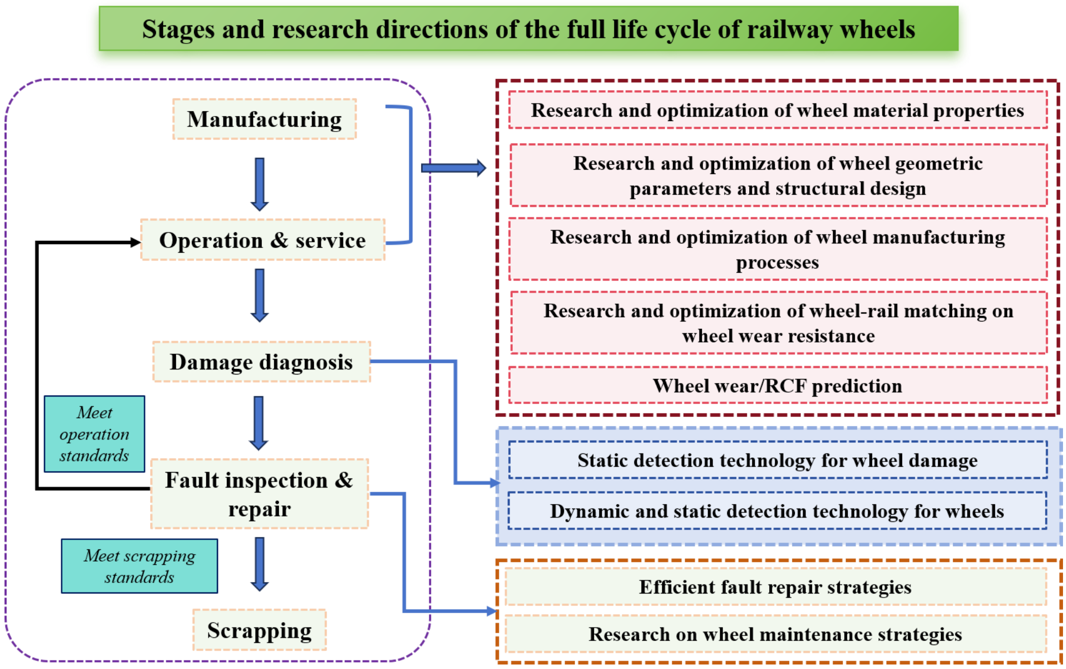

Fig 1 Full lifecycle of train wheels and optimisation directions

From this standpoint, a life cycle-based review is valuable not only for organising existing knowledge, but also for clarifying the technical relationships among degradation mechanisms, condition indicators, predictive models, and maintenance strategies. The stage-based framework shown in Fig. 1 is therefore adopted to structure the present review. Section 2 examines the key design and

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manufacturing factors that define the initial wheel state. Section 3 reviews in service degradation mechanisms and life prediction methods associated with wear and RCF. Section 4 discusses condition monitoring and maintenance interventions that support condition-based maintenance. Section 5 summarises the principal findings and highlights priority directions for future research. The purpose of this review is not just to compile previous studies, but to provide a clearer technical logic for route specific and system specific wheel life management in modern railway systems.

2. Design and manufacture of railway wheels

Railway wheels transmit vertical and lateral loads, provide guidance and transfer traction and braking torque. Design and manufacturing choices therefore influence safety margin, degradation rate and maintenance demand over service life. Section 2 reviews four controllable levers before wheels enter service: material and microstructure, contact geometry through tread and flange design, manufacturing route with heat treatment and residual stress control, and durability under regional environments (Fig 2).

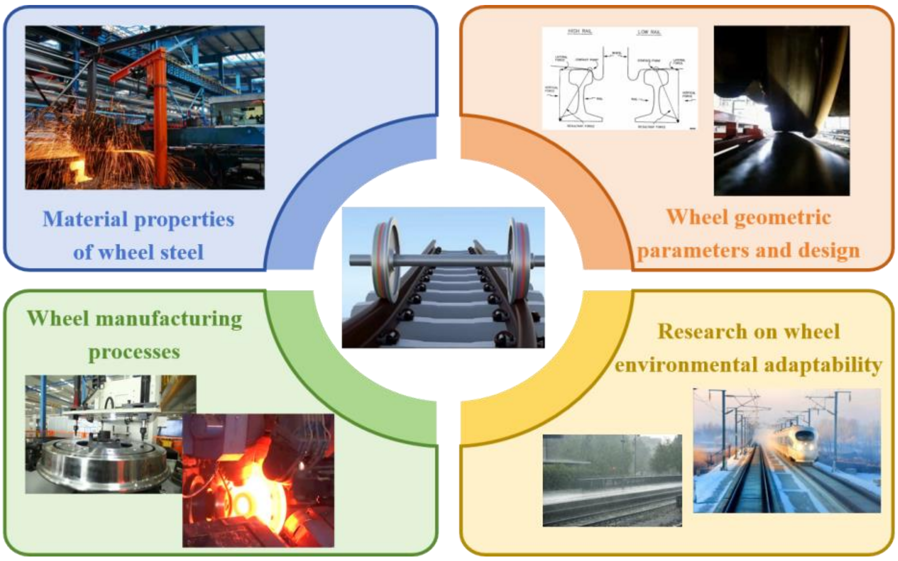

Fig 2 Research directions for wheel production and design

2.1 Wheel materials, microstructure and alloy design

The material design of railway wheels has long been recognised as a key factor governing service performance and damage evolution. Material capability affects not only wear resistance, fatigue strength, fracture toughness, and resistance to thermally induced surface damage, but also the near surface response under repeated rolling contact, which plays a decisive role in wheel life. At the same time, wheel material behaviour is strongly influenced by wheel-rail pairing, because hardness ratio and work hardening capacity shape wear partition and damage mode at the contact interface. For this reason, research on wheel materials has extended from conventional pearlitic steels towards bainitic, carbide free bainitic, and dual hardness concepts, with the aim of improving crack resistance and near surface deformation characteristics without unacceptable loss of toughness. More recently, surface engineered systems and graded architectures have also attracted attention as possible routes for localised performance development in the contact layer. This section therefore reviews the main material systems and design strategies that have been explored for improving the service capability of railway wheels.

2.1.1 Effects of chemical composition on wear and fatigue resistance

Pearlitic steel, characterised by a microstructure composed of pearlite, has long been widely used in railway wheels and rails. Owing to its lamellar ferrite/cementite structure, pearlitic steel shows excellent work-hardening capability and resistance to plastic deformation under rolling-sliding contact conditions. Studies have shown that by tailoring the carbon content and microalloying elements, such as Si, Mn, and Cr; it is possible to effectively refine the interlamellar spacing and optimise hardness distribution, thereby improving the wear resistance and rolling contact fatigue resistance of wheel steels. Extensive research has been conducted in this regard. Liu et al. [5] investigated the matching characteristics of four different wheel materials against rail steel and found that, as the carbon content of the wheel increased, the wheel hardness increased and the wear loss decreased, whereas the wear of the mating rail gradually increased. Chen et al. [6] carried out rolling contact simulation tests on four-wheel steels with carbon contents ranging from 0.51% to 0.72%. Their results showed that, with increasing carbon content, the hardness of the wheel increased, and the wheel wear depth gradually decreased as wheel hardness increased. Wang et al. [7] also reported that increasing carbon content can improve wheel hardness and wear resistance, but at the expense of aggravated rail wear. However, as the carbon content in wheel steel increases, the hardness and strength of the steel increase while its toughness decreases, resulting in reduced fatigue resistance of the wheel [8]. Although increasing carbon content can improve wheel hardness and reduce wheel wear, high carbon levels limit further hardness improvement and deteriorate toughness, making it difficult to achieve a balanced combination of strength and toughness and thereby weakening the wheel's resistance to fatigue damage.

In addition to adjusting the carbon content, the addition of microalloying elements such as silicon (Si), manganese (Mn), and chromium (Cr) can also improve wheel strength. Sun et al. [9] compared the wear behavior of wheels made from conventional CL60 steel and newly developed CL60 steel with optimised Si, Mn, and Cr contents and additional Mo and V. The new CL60 steel wheels have been found and shown lower wear loss, total wear rate, and plastic deformation layer thickness than the original CL60 steel wheels. Pan et al. [10] proposed that increasing the Si content can improve the strength of wheel steel without impairing its plasticity and toughness. Zeng et al. [11] designed and prepared an improved wheel steel with high Si, high Mn, and low Cr contents, which revealed higher strength without compromising toughness. Demisie et al. [12] increased the contents of Si, Mn, and C in wheel steel and found that the steel achieved higher strength and hardness while retaining its original toughness. Carbon plays a decisive role in determining the properties of wheel steel. An increase in carbon content is beneficial for improving wear resistance, and a good balance between strength and toughness can be achieved when the carbon content is maintained within the range of 0.69%-0.74%. In addition to carbon, microalloying elements such as Si and Mn also apply significant effects on wheel steel performance; however, excessive additions can reduce wheel toughness [13].

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Overall, the optimisation of wheel steel has progressed from single carbon content regulation to a medium carbon and microalloying based design strategy, as shown in Fig. 3. Through precise control of trace element composition and microstructural tailoring, wear resistance can be improved while maintaining adequate toughness and fatigue performance. Meanwhile, increasing wheel strength g improves resistance to crack initiation, but tends to reduce resistance to crack propagation. Such optimisation strategies therefore continue to face an inherent trade-off between strength improvement and crack growth resistance. In particular, under conditions of high carbon or high alloy content, the accompanying reduction in material toughness limits the applicability of such steels in complex service environments associated with high speed and heavy-haul operations.

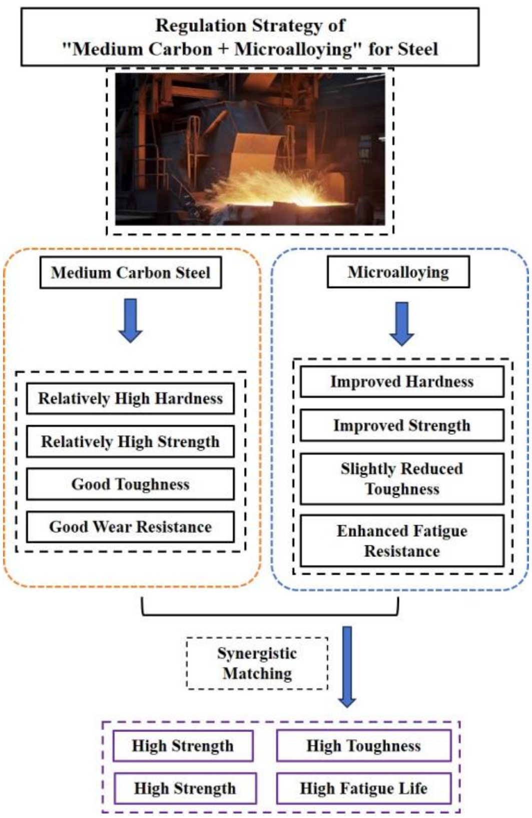

Fig 3 Regulation strategy of "Medium Carbon + Microalloying" for steel

2.1.2 Pearlitic and bainitic wheel and rail steels, wear mechanisms and material pairing

At present, the improvement of pearlitic steel properties has gradually approached its theoretical limit. Although increasing carbon content can increase wear resistance, it often comes at the expense of toughness and may aggravate rail wear or even alter fatigue damage mechanisms. Therefore, while compositional optimisation of conventional pearlitic steels still holds some potential, it is difficult to achieve breakthrough improvements in performance. Given that research on developing the mechanical properties of pearlitic steels has reached its theoretical ceiling, bainitic steels offering a combination of high strength, high toughness, and excellent wear resistance, have emerged as promising alternatives [14]-[15]. Therefore, increasing attention has been directed toward bainitic steels, and extensive studies have been conducted worldwide to compare the wear behavior of steels with these two distinct microstructures. Singh et al. [16] investigated the mechanical properties of bainitic and pearlitic steels and found that bainitic rail steel exhibits superior strength, hardness, and impact toughness compared with pearlitic steel; however, its wear resistance was inferior. Lee et al. [17] compared the sliding wear behavior of bainitic and pearlitic steels and reported that, although bainitic steel has a higher initial hardness, pearlitic steel undergoes significant work hardening during wear, resulting in better wear resistance. Similarly, Viáfara et al. [18] confirmed through sliding wear tests that pearlitic steel exhibits superior wear resistance, which may be attributed to its stronger work-hardening capability. Zapata et al. [19] adjusted bainitic and pearlitic steels of different compositions to the same hardness level and conducted rolling wear tests. Under low load conditions, no significant difference in wear was observed; however, due to its superior work-hardening capability, bainitic steel exhibited better wear resistance in the later stages of testing. In recent years, considerable attention has been paid to carbide-free bainitic steels with high Si content for wheel-rail applications. Hasan et al. [20] studied the rolling/sliding wear behavior of two newly designed low-carbon, continuously cooled carbide-free bainitic steels and compared them with pearlitic steel. The results showed that bainitic steels indicates superior wear resistance, which increases with initial hardness. Sharma et al. [21] compared the wear performance of medium-carbon bainitic steel and pearlitic steel, demonstrating that bainitic steel possesses superior mechanical properties and improved wear resistance due to its higher hardness and strength. Chen et al. [22] investigated the evolution of near-surface microstructures and properties during sliding wear under different cooling conditions and found that bainitic steel exhibits better wear resistance than pearlitic steel under identical conditions. However, Liu et al. [23] reported that, despite the higher initial hardness of carbide-free bainitic rail steel, its wear loss exceeded that of pearlitic steel. The inferior wear resistance of bainitic steel was attributed to its relatively weaker work-hardening capability and the absence of a white etching layer (WEL) on its worn surface, whereas such a layer forms on pearlitic steel and contributes to improved wear resistance. Rezende et al. [24] studied wheel steels with different microstructures and found that bainitic steels exhibit lower mass loss, higher hardness, and greater capacity for accommodating plastic deformation. Moreover, the delamination wear process in bainitic steels develops more slowly, and crack propagation tends to remain closer to the surface. These findings indicate that highly localised plastic deformation in the surface layer of bainitic steel effectively suppresses crack initiation and propagation into the material depth. Zhang and Gu [25] developed a carbide-free bainitic steel wheel and demonstrated through rolling wear tests that the bainitic wheel-pearlitic rail combination exhibits superior wear performance compared with the pearlitic wheel-pearlitic rail pairing.

Overall, current studies indicate that wear behaviour is governed not only by initial hardness, but also by work hardening capacity, plastic deformation, and the evolution of near surface microstructures. A simple one to one correlation between hardness and wear resistance cannot be assumed for steels with different microstructures, while wear performance is also influenced by the counterpart material. At present, no consistent conclusion can be drawn regarding the relative wear resistance of pearlitic and bainitic steels. In addition, comparative studies under representative service conditions remain insufficient. Future work can therefore focus on the systematic assessment of the overall service performance of wheel steels with different microstructures through full scale field testing and wheel–rail system experiments.

Table 1 Comparison of properties between pearlitic steel and bainitic steel

Steel Type	Strength &Hardness	Fatigue Resistance	Crack Growth Rate	Ductility /Toughness	Wear Resistance	Industrial Application Status
Pearlitic Steel	Relatively high	Relatively high	Relatively fast	Relatively high	Excellent	Very mature
Bainitic Steel	High	High	Relatively slow	High	Moderate	Under promotion

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2.1.3 Emerging material concepts and surface engineered systems

To meet the future demands of railway transportation for lightweight structures, long service life, and ultra-high reliability, exploring novel solutions beyond traditional steel material systems has become an emerging trend. Composite materials, particularly metal matrix composites (MMCs) realised through architectural design and surface modification technologies, having significant potential for simultaneously improving strength, toughness, and wear resistance through microstructural innovation. Although these materials have not yet been widely applied to railway wheels, they provide valuable insights for the design of advanced surface engineering solutions. At present, notable progress has been achieved in the architectural design of metal matrix composites (as shown in Fig. 4).

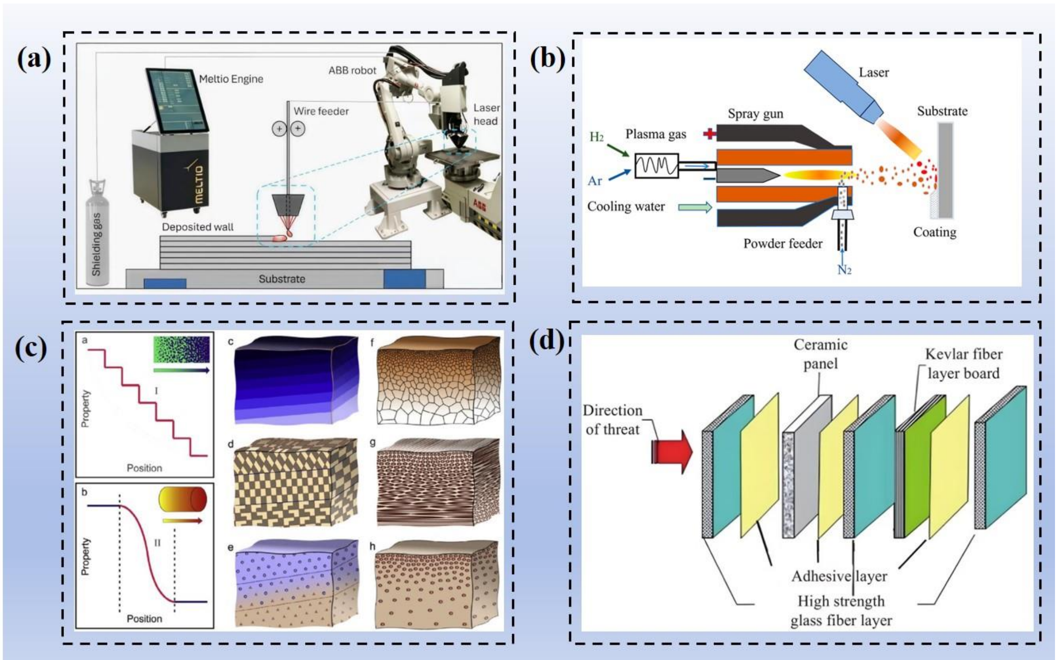

Fig. 4 Main research directions of advanced railway wheel materials: (a) and (b) Surface modification and coating strengthening technologies, (c) Manufacturing technologies for functionally graded materials (FGMs), (d) Layered/Composite structural material technologies

In terms of surface modification and coating reinforcement technologies, Movassagh-Alanagh et al. [26] used multilayer nanocomposite coatings on stainless steel using cathodic arc evaporation, combined with plasma nitriding of the substrate, thereby improving coating-substrate bonding strength and improving wear resistance. Ding et al. [27] developed a novel multiscale WC-10Co4Cr coating via high-velocity oxygen fuel (HVOF) spraying, consisting of nano-, submicron-, and micron-sized WC particles embedded in a CoCr matrix. The coating exhibited low porosity (≤0.32%) and high fracture toughness. Ding et al. [28] fabricated h-BN/CaF_2/Fe composite coatings using laser cladding and evaluated their wear and rolling contact fatigue resistance through hardness and residual stress measurements. The results indicated that optimised compositional ratios increasing both wear and fatigue resistance. Wang et al. [29] produced a ~10 μm thick nanocrystalline surface layer on low-carbon steel via surface mechanical grinding, resulting in a gradual hardness increase from the substrate to the surface. Under low loads, the friction coefficient was reduced, improving wear resistance. Wang [30] further demonstrated that laser quenching forms a hardened martensitic layer of controlled depth, leading to a substantial reduction in wear of wheel-rail samples. Surface modification and coating technologies improve material performance by altering the substrate surface or depositing hard, wear-resistant phases, thereby improving surface hardness and wear resistance. Regarding gradient-structured materials, Zhao et al. [31] fabricated an Fe-based NbC gradient layer using hot-press sintering and in situ reaction techniques. The resulting structure presented micro-/nano-scale gradient characteristics: a surface layer rich in micro-/nano-sized NbC particles and a subsurface NbC-Fe gradient region. Such a design integrates ceramic reinforcement and gradient toughening mechanisms, alleviating the common strength-toughness trade-off in ceramic-metal composites. Bai et al. [32] fabricated a dense TiC-Fe gradient coating on cast iron using a two-step in situ reaction method. The coating showed a gradient decrease in hardness and elastic modulus from the surface to the interface, accompanied by a gradient increase in fracture toughness. Gradient structures mitigate interfacial mismatch between hard phases and the matrix, enabling improved hardness without sacrificing overall toughness. For layered and composite structures, Sadeghi et al. [33] produced a laminated composite consisting of one magnesium alloy layer and two stainless steel layers via reactive transient liquid phase bonding, achieving both high specific strength and ductility. Kang et al. [34] fabricated a laminated structure using rolling bonding and high-pressure torsion, composed of TWIP steel sandwiched between two IF steel layers (IF-TWIP-IF), demonstrating high surface strength, hardness, and excellent ductility. Wu et al. [35] developed TiBw/Ti composites with various heterogeneous architectures, including quasi-continuous network, dual-scale network, layered-network hybrid, and 3D interconnected reinforcement structures, achieving a ~5-fold increase in plasticity compared with pure titanium. The synergistic deformation mechanisms in layered composites improve the strength-ductility balance.

Table 2 Comparative evaluation of advanced material strengthening and manufacturing technologies

Technology Type	Cost	Performance Improvement Mechanism	Key Issues	Application Areas	Overall Evaluation
Surface Modification and Coating Strengthening Technologies	Low	Improves surface properties (wear, corrosion, fatigue resistance)	Interface failure (delamination, cracking), limited thickness	Tools, bearings, molds, aerospace components	Most mature and cost-effective
Manufacturing Technologies for Functionally Graded Materials (FGMs)	High	Continuous gradient in composition and properties	Complex manufacturing, high cost, limited standardisation	Aerospace, thermal barrier coatings, nuclear engineering	High potential for advanced applications
Layered / Composite Structural Material Technologies	Medium–High	Combines different materials for synergistic properties	Delamination, interface reliability, anisotropy	Aerospace structures, armor materials, lightweight design	Highly designable but interface-sensitive

In summary, existing studies show that rational structural design, combined with advanced fabrication processes involving gradient, multilayer, and surface engineered architectures in metallic materials, can improve key mechanical properties, including strength, hardness, toughness, and wear resistance. Such strategies are effective in mitigating the intrinsic conflict between strength and toughness, while also promoting stronger interfacial bonding between coating and substrate and improving overall service performance. These findings provide an important theoretical basis and technical framework for the development of high-performance metal-based composites intended for severe operating conditions. In view of such advantages, considerable potential exists for the future application of such materials in railway wheel manufacturing and the improvement of long-term service durability.

2.2 Wheel geometry, profile design and contact control

Wheel wear resistance is determined not only by material properties but also by geometric design and key structural parameters. Wheel geometry sets the wheel-rail contact conditions and therefore affects vehicle dynamics, including stability and curving behaviour. Wear then modifies tread and flange geometry during service, leading to progressive change in contact geometry, contact stress distribution, and the resulting wear and fatigue response. Given the scale of railway networks and the cost of rail renewal, wheel profile design and reprofiling practice often provide a more practical and economical route for managing wheel-rail contact conditions than altering rail profiles.

2.2.1 Tread profile design and optimisation methods

Compared with the lengthy development cycle and relatively difficult experimental validation of wheel materials, optimising wheel structural parameters under constant material conditions represents a more feasible approach for improving wheel wear performance. Therefore, various wheel profile optimisation methods have been proposed.

(1) Wheel profile optimisation based on wheel-rail geometric contact characteristics

Shevtsov et al. [36] proposed a wheel profile design framework based on wheel-rail geometric contact characteristics. This approach employs numerical optimisation techniques and adopts a response surface method based on multipoint approximation to minimise the deviation between the target rolling radius difference (RRD) function and the actual RRD function. Cui et al. [37] proposed a forward optimisation method for wheel profiles based on the weighted normal gap at wheel-rail contact points. Taking the wheel-rail combination of an LMA wheel profile and a CHN60 rail as an example, the optimised profile improved the distribution of contact points and reduced wheel-rail forces. Santamaria et al. [38] optimised wheel profiles based on an ideal equivalent conicity curve, achieving a more uniform distribution of contact points within the effective contact region, thereby reducing contact stress and improving wear performance. Yao et al. [39] used the dispersion of equivalent conicity for wheel profiles matched with CN60 and CN60N rails as the optimisation objective. By applying the fast non-dominated sorting genetic algorithm (NSGA-II), the lateral positions of arc centres near the rolling circle were improved. The optimised profiles reduced equivalent conicity dispersion and improved adaptability to different rail profiles and track conditions.

(2) Wheel profile optimisation based on vehicle dynamic performance

Cui et al. [40] proposed a multi-objective optimisation method aimed at reducing

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lateral wheelset forces and retaining running stability, thereby defining geometric design requirements for wheel profiles. Particle swarm optimisation (PSO) was used to obtain a tread profile that satisfies operational safety requirements. Fu [41] applied a multi-population genetic algorithm (GA) to optimise wheel profiles for freight trains under acceleration conditions, using comprehensive vehicle dynamic parameters as design objectives. The study investigated the matching performance between equivalent conicity and vehicle/track parameters, identifying the optimal equivalent conicity as a constraint. The optimised profiles improved both dynamic performance and wear behavior. Hou et al. [42] optimised wheel profiles based on the original LMA profile using a Gaussian function correction (GFC) method combined with a Kriging surrogate model (KSM). This method mainly modifies the flange root region to improve curving performance and reduce wheel wear.

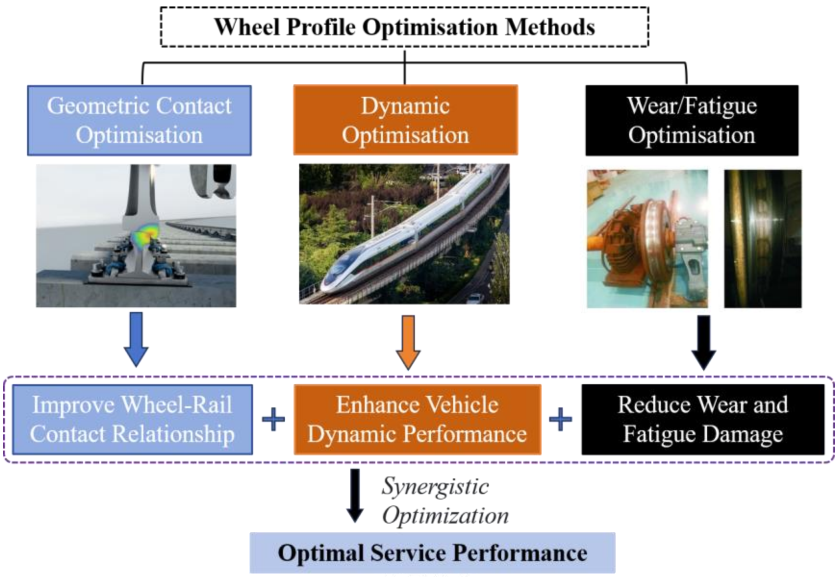

Figure 5 Wheel profile optimisation methods

(3) Wheel profile optimisation based on wear performance

Choi et al. [43] optimised the wheel flange profile using the NSGA-II algorithm with the objective of reducing flange wear and surface fatigue. The optimised profile demonstrated improved performance, with reduced flange wear and fatigue damage. Pacheco et al. [44] proposed a wheel profile optimisation method considering both rolling contact fatigue (RCF) and wear performance. Using NSGA-II, three optimised profiles were obtained with reduced wear indices and substantially improved fatigue indices. Lu et al. [45] established a nonlinear numerical optimisation model for wheel profiles based on a backpropagation (BP) neural network, with wheel arc parameters as input variables and circumferential tread wear rate as the objective function. A single-objective, multi-variable, multi-constraint optimisation approach was employed to minimise tread wear rate. Firlik et al. [46] proposed a biologically inspired black-box optimisation algorithm (BBOA) for tread profile optimisation. The optimised profiles showed improved wear indices and derailment coefficients compared with currently used profiles.

In summary, wheel profile optimisation has become an important means of improving wheel-rail interaction and extending wheel service life. Optimisation methods based on geometric contact characteristics offer advantages in computational efficiency and modelling simplicity, but often cannot reflect vehicle dynamic behaviour under actual operating conditions. By contrast, methods based on vehicle dynamic performance can provide a more comprehensive assessment of wheel-rail forces, running stability, and curving performance, although they impose higher demands on computational cost and model accuracy. In recent years, advances in artificial intelligence have promoted growing interest in intelligent multi objective optimisation, making it possible to achieve a better balance among wear, rolling contact fatigue, and vehicle dynamic performance. Future research is therefore expected to move towards multidisciplinary coupled modelling, intelligent multi objective optimisation, and data driven methods, with the aim of achieving coordinated optimisation of overall wheel-rail system performance.

2.2.2 Equivalent conicity and wheel-rail contact geometry

As train operating speeds continue to increase, wheel-rail interaction, as a fundamental issue in vehicle-track system dynamics, has become significant and has received sustained attention. Wheel-rail contact geometry lies at the core of wheel-rail interaction research. Among the relevant geometric parameters, equivalent conicity plays a particularly important role in supporting both the dynamic behaviour of vehicles and the wear characteristics of the wheel-rail interface. Its magnitude directly influences the distribution of contact points and the associated contact stress level, making it a key parameter in wheel profile optimisation. Appropriate control of equivalent conicity can reduce wear, prolong the service life of wheel-rail systems, and improve vehicle running safety and stability.

In terms of calculation and characterisation methods for equivalent conicity, Gan [47] employed simplified, harmonic, and UIC519 methods to calculate the equivalent conicity of widely used domestic wheel profiles. A dedicated software tool for wheel–rail contact analysis was developed, and it was shown that the harmonic method and the UIC519 algorithm provide more accurate results. Qian et al. [48], based on the wavelength formula of wheelset hunting motion, used a method for calculating equivalent conicity in turnout regions. They also proposed a nominal equivalent conicity corresponding to the most probable lateral displacement of the wheelset to evaluate wheel-rail contact geometry in these regions. Damsongsaeng et al. [49] utilised a dual extended Kalman filter to estimate equivalent conicity in real time for condition monitoring and stability control. Xu and Dong [50], based on nonlinear wheel-rail contact theory, investigated the influence of nonlinear equivalent conicity on the running behavior of EMUs under conditions of identical nominal equivalent conicity. Their results showed that even with the same nominal value, significant differences in wheel-rail interaction may exist. Accordingly, a new evaluation approach was proposed in which statistical data were used to derive the nonlinear coefficient and nonlinear equivalent conicity over the range of 1 to 6 mm. Both field tests and numerical simulations showed that nominal equivalent conicity cannot accurately represent wear related contact conditions, whereas the proposed indices, which combine nominal conicity with the slope of the conicity curve, can more effectively characterise the nonlinear features of wheel-rail contact. Regarding the relationship between

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equivalent conicity and vehicle dynamics, Kulkarni et al. [51] investigated the influence of wheel–rail contact conditions on vehicle dynamic performance using NP-$\lambda_3$mm (equivalent conicity at 3 mm lateral displacement) scatter plots derived from a conicity function database. The results indicated a negative correlation between $\lambda_3$mm and NP; higher $\lambda_3$mm values correspond to more negative NP values, which may reduce the nonlinear critical speed of the vehicle. Gerlici et al. [52] studied the matching behavior between different wheel profiles and rails and confirmed, through simulations, a significant correlation between equivalent conicity and critical speed. In terms of optimisation design based on equivalent conicity, Chen et al. [53] used measured profiles of a 60D40 switch rail as optimisation samples and obtained an optimised rail profile by inversely calculating from reduced equivalent conicity curves. This method, based on the relationship among equivalent conicity, rolling radius difference (RRD), and rail profile slope, improves ride stability when passing through turnouts and enables effective conicity optimisation. Ersson et al. [54] proposed a new gradient index profile (GIP), which decomposes equivalent conicity into wheel and rail components, allowing independent constraints on wheel and rail profiles and enabling more precise prediction and control of equivalent conicity.

Overall, existing studies indicate that equivalent conicity, as a concise, practical, and widely used parameter for characterising wheel-rail contact geometry, plays a pivotal role in wheel-rail profile design, dynamic performance assessment, and in service condition monitoring. Its engineering application requires careful consideration of operating conditions, track and turnout geometry, and the nonlinear evolution of contact states during wear. On this basis, profile optimisation guided by equivalent conicity, in combination with wheel-rail contact analysis and vehicle system dynamic simulations, remains an important approach for improving vehicle stability and wear performance.

2.3 Manufacturing processes and heat treatment

The increasingly severe demands imposed by heavy haul service, high speed operation, and harsh environmental conditions have made integrated control of forging, heat treatment, and property distribution a key issue in railway wheel design. Modern process design must satisfy not only the requirements for bulk strength and toughness, but also the need for controlled rim hardness, stable near surface behaviour, and a favourable residual stress state. Against this background, wheel concepts based on dual hardness and hardness gradients have emerged as promising strategies for improving resistance to wear, rolling contact fatigue, and thermally induced surface damage.

2.3.1 Forging and heat treatment, microstructure and residual stress

As a typical large load-bearing component, the service performance of railway wheels is governed by their microstructure and mechanical properties. Heat treatment serves as a core technological approach for tailoring microstructural features and property distributions. Through rational design of heat treatment routes, it is possible to achieve a synergistic improvement in wear resistance and rolling contact fatigue (RCF) performance while maintaining overall wheel strength. As a results, optimisation of heat treatment processes based on service requirements has become a key research focus in this field.

Tao et al. [55] proposed an improved quenching process integrating spray control with phase transformation characteristics. By introducing a holding stage at 700 °C for 600 s prior to conventional spray quenching, bainite transformation was promoted and its volume fraction increased. The results showed that the process reduced the performance gradient between the surface and core, improving the overall strength-toughness balance by around 20%. Zhang et al. [56] investigated the effect of annealing at 500 °C on pearlitic wheel steel and found that annealing relieved local residual stresses and reduced stress concentration, thereby improving fracture toughness and fatigue performance. Gao et al. [57] optimised the quenching-tempering process by regulating bainitic ferrite content and retained austenite stability. By adopting a combined cooling path of water mist spraying and air cooling, proeutectoid ferrite precipitation was suppressed while bainite transformation was promoted, resulting in a synergistic improvement of strength and toughness. Liu et al. [58] conducted quenching-tempering experiments on CL60 wheel steel and revealed the influence of tempering temperature on microstructural evolution and wheel-rail matching performance. As the tempering temperature increased, the microstructure transformed from tempered troostite to tempered sorbite, accompanied by a gradual decrease in hardness. Meanwhile, the wheel-rail wear rate exhibited a trend of first increasing and then decreasing, with the highest wear corresponding to tempered sorbite. Zhang et al. [59] studied the effect of plasma quenching parameters on contact fatigue performance and found that martensite formation and residual compressive stress induced by rapid heating and cooling could increase fatigue life by approximately 30%. However, excessive local residual tensile stress may also trigger crack initiation and spalling failure. Wang et al. [60] proposed a composite process combining laminar plasma quenching and tempering, which reduces lattice distortion and optimises microstructure, thereby suppressing RCF damage while maintaining wear resistance. Li et al. [61], based on high-throughput characterisation techniques, used a quantitative method for analysing the distribution of composition, microstructure, and hardness in wheel materials. The study revealed the gradient distribution of microstructure and properties from the tread surface to a depth of 50 mm and applied ma statistical correlation between ferrite area fraction and microhardness. In addition, the application of finite element methods and intelligent algorithms enables rapid optimisation of heat treatment parameters and multi-scheme comparison while reducing experimental costs, providing important support for intelligent heat treatment. Chen and Lingamanaik [62] analysed the formation mechanism of residual stress during spray quenching using finite element methods, highlighting the significant influence of quenching time, spray position, and cooling configuration on temperature evolution and phase transformation behavior. Cuperus et al. [63] demonstrated through nonlinear finite element simulations that accurate prediction of residual stress requires comprehensive consideration of creep behavior, latent heat of phase transformation, transformation strain, and complex heat transfer boundary conditions. Tian et al. [64] developed a thermos-phase transformation coupled model, revealing the influence of asymmetric cooling on microstructural evolution and hardness distribution, and identifying spray angle as a key parameter for controlling

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temperature history and hardness uniformity. Furthermore, combined experimental and simulation analyses showed the non-uniformity of rim hardness distribution and clarified the influence of local hardening (or gradient hardness) on stress and wear behavior. Xiong et al. [65] evaluated five machine learning algorithms for predicting steel properties and found that random forest regression achieved the best predictive performance. Further research utilised the mapping relationship between tempering temperature and material properties using machine learning techniques.

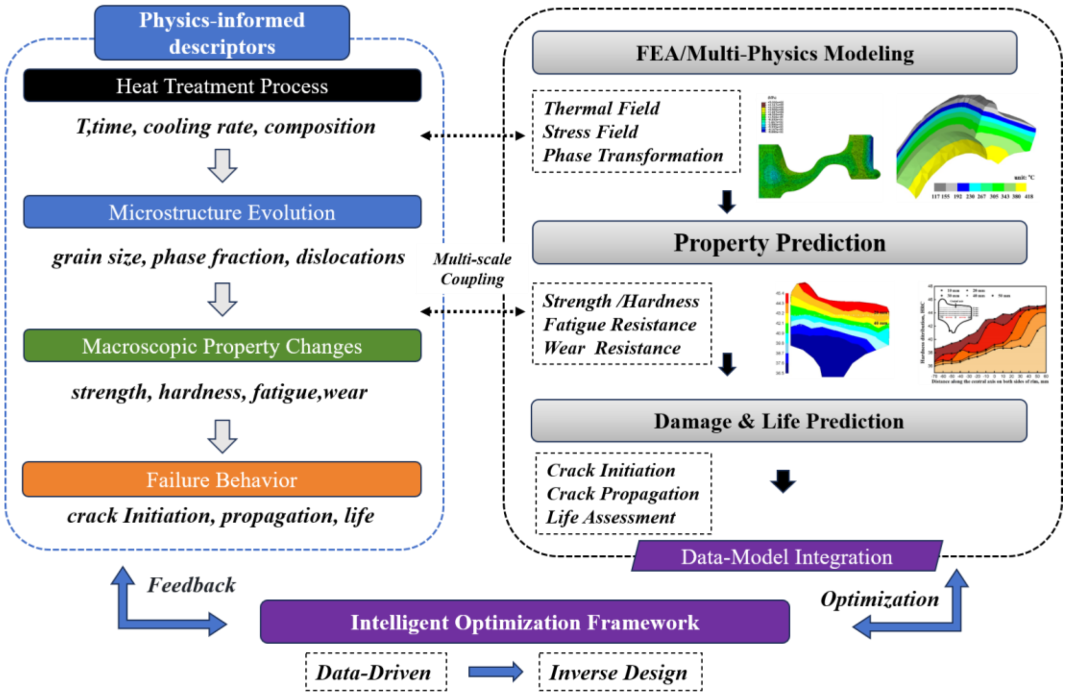

Figure 6 Framework of coupling mechanism between wheel heat treatment process, microstructure evolution, property response and finite element intelligent optimisation [62]

Overall, existing studies indicate that optimisation of quenching paths, control of cooling rates, and the introduction of multistage heat treatment strategies make it possible to achieve coordinated regulation of multiphase microstructures, including bainite, pearlite, and retained austenite, thereby improving the strength, toughness, and wear resistance of wheel materials. As shown in Fig. 6, research on wheel heat treatment has gradually progressed from traditional empirical process design to a more systematic framework centred on microstructural regulation, performance optimisation, and intelligent prediction. At the same time, increasing attention has been directed towards the relationship between microstructural evolution and macroscopic properties, which has clarified the critical roles of hardness gradients, residual stress distribution, and microstructural features in wheel-rail service behaviour. However, several limitations remain. Most existing studies focus on individual process parameters or localised microstructural control, while systematic optimisation from a full life cycle perspective is still lacking. In addition, efficient coupling between experimental investigation and numerical simulation has yet to be achieved, particularly in the accurate prediction of multiphysics phase transformation behaviour and residual stress evolution. Furthermore, the mechanisms by which heat treatment affects wheel–rail matching and service damage evolution remain insufficiently understood.

2.3.2 Dual hardness and surface hardening technologies.

Local hardening or dual-hardness treatment of railway wheels is commonly achieved through plasma quenching. Plasma quenching is a surface strengthening technique belonging to the category of thermal surface hardening. Its core principle involves rapid heating of the metal surface using high-temperature plasma energy, followed by rapid cooling through self-conduction of the workpiece, thereby inducing phase transformation in the surface layer (e.g., formation of high-hardness martensite). The process improves surface hardness, wear resistance, and fatigue strength while maintaining good toughness in the substrate. Isakaev et al. [66] developed a computer-controlled plasma surface strengthening technology capable of locally hardening the wheel tread and flange. The process increased surface hardness from approximately 255 HB to 420-450 HB, while improving wear resistance by 2–3 times and fatigue resistance by about 1.5 times. Kanaev et al. [67] systematically investigated the mechanisms and experimental results of plasma quenching, demonstrating that it forms a non-equilibrium surface layer on the wheel flange and rim, thereby improving surface hardness and wear resistance. Yusupov et al. [68] conducted comparative experiments between plasma-quenched and untreated freight car wheels and successfully applied this technology to locomotive and passenger wheels, improving flange wear resistance and extending service life. In recent years, with the successful application of kilowatt-level fibre lasers, laser heat treatment has emerged as an advanced alternative. Compared with plasma quenching, laser heat treatment offers several advantages, including low strain and stress levels, high scanning speed, capability for deep processing, and low maintenance cost. As a results laser-based processes are gradually replacing plasma quenching in practical applications. Bogdanov et al. [69] compared laser quenching and plasma quenching techniques for improving wheel tread strength and contact fatigue resistance, and determined the optimal process parameters for laser heat treatment of wheel steel, achieving superior surface wear resistance. Gubenko et al. [70] proposed a method to improve tread wear resistance via localised laser treatment and analysed the effects of pulsed and continuous laser modes on the microstructure and properties of wheel steel. Their results confirmed that laser processing effectively improves surface hardness and wear resistance. Cao et al. [71] investigated the microstructure, wear performance, and rolling contact fatigue (RCF) behavior of wheel–rail materials after laser dispersed quenching. The results showed that the treated regions exhibited a uniform martensitic structure with increased surface hardness, thereby improving wear resistance. Fayzibaev et al. [72] proposed a method to calculate the depth of the strengthened layer on wheel rolling surfaces. By applying controlled impact forces using a dedicated impact device, plastic deformation is induced in the flange surface layer, thereby increasing surface hardness. Gubenko et al. [73] compared wheel steel subjected to induction thermal cycling with untreated material and found that the formation of sorbite structures and associated compressive stresses improved fatigue resistance.

In summary, local hardening and dual hardness wheel structures are achieved through surface heat treatment technologies, which rely on regulating near surface microstructures to balance wear resistance and fatigue performance. Plasma quenching can increase surface hardness and improve wear resistance, and has already been widely adopted in engineering practice. However, the non-uniform residual stress state introduced by such treatment may increase the risk of fatigue damage. By contrast, laser heat treatment, owing to its controllable energy input and reduced thermal effect, shows greater potential for optimising microstructure and residual stress distribution, and is emerging as a major development direction. At the same time, methods such as impact strengthening and induction thermal cycling reflect a broader trend towards multi process synergistic improvement. Despite such progress, significant challenges remain in understanding the multiscale coupled mechanisms governing dual hardness wheels and in predicting their long-term service performance, indicating a continued need for more precise control and intelligent optimisation.

2.4 Environmental durability and service conditions

As railway systems extend across broader geographic regions and operate under increasingly demanding conditions, environmental adaptability has emerged as an important issue in railway wheel design. Wheels are required to withstand not only rolling contact fatigue, wear, impact, and thermal loading, but also environmental exposure associated with low temperature, humidity, salinity, and contamination. Such factors can alter material response and damage evolution, particularly in relation to embrittlement and corrosion related deterioration, thereby affecting the stability and durability of wheel service performance. A clear understanding of environmental effects is therefore essential for the development of wheel materials and designs suitable for different operating regions and service conditions.

2.4.1 Low temperature service, embrittlement and damage mechanisms

Existing studies indicate that low-temperature environments affect wheel service performance mainly through three aspects: adhesion behavior, plastic deformation, and material toughness. Shi et al. [74] reported that under dry conditions, low temperatures suppress surface oxidation on the wheel, thereby increasing the adhesion coefficient. However, under both ambient and low-temperature conditions, the presence of water, oil contaminants, or antifreeze reduces the adhesion coefficient to low levels, and low temperatures prolong the adhesion recovery process under water-mediated conditions. Zhou et al. [75] found through wheel–rail experiments that decreasing temperature can reduce wheel wear due to the formation of a wear debris layer. However, both increases and decreases in ambient temperature can aggravate rail wear. Furthermore, decreasing temperature intensifies plastic deformation and work hardening on the wheel–rail contact surface. At -40 °C, a white etching layer (WEL) induced by severe plastic deformation was observed on the wheel surface. Although this layer increases surface hardness, it reduces material toughness, making the material more prone to brittle fracture and spalling.

Ostash et al. [76] demonstrated that medium- to high-strength railway wheel steels containing fatigue crack-like defects exhibit low-temperature embrittlement (down to -60 °C) under high cyclic loading amplitudes, particularly when the fatigue crack growth rate exceeds 10^{-7} m/cycle. Li et al. [77] reported that, under both dry conditions and with the use of friction modifiers, temperature variation does not affect the degree of wheel fatigue damage. In all temperature conditions, friction modifiers can reduce wheel wear rates while maintaining relatively mild rolling contact fatigue (RCF) damage; however, under low-temperature conditions, rail wear may be aggravated. These results indicate that the proper use of friction modifiers plays a positive role in improving wheel performance in low-temperature environments. Liang et al. [78] introduced nanoscale tungsten carbide (WC) particles under low tempering temperatures, achieving a synergistic effect of reduced lattice distortion in bainitic ferrite, precipitation strengthening, and improved toughness, while maintaining the content and stability of retained austenite. The process improved the overall mechanical properties of the steel by 17% and increased impact toughness by 41%, thereby improving wheel service performance. In summary, for cold region applications, the use of high toughness wheel steels, together with appropriate friction modification strategies, can improve wheel service performance.

2.4.2 Hot humid service, corrosion, adhesion and wear

Railway wheels operate under long-term exposure to open environments, where humid and hot conditions affect their service performance by altering interfacial chemical reactions and wear mechanisms at the wheel-rail contact. Rong et al. [79] investigated the influence of environmental humidity on adhesion characteristics and damage behavior at the wheel-rail interface under different weather conditions. The results showed that humidity has a pronounced effect on adhesion behavior. Under low-humidity conditions, fatigue wear dominates; as humidity increases, abrasive wear becomes more severe, since oxide debris acts as abrasive particles and accelerates wear. Under high-humidity conditions, a friction-reducing layer forms, which protects the rolling surface from excessive wear. However, such environments are unfavourable for safe railway operation, as high temperature and humidity promote the formation of tribochemical products (a mixture of iron oxides and water molecules), leading to a significant reduction in the adhesion coefficient between wheel and rail. He et al. [80] studied the effects of environmental humidity on the adhesion characteristics and damage behavior of CL60 wheel steel. Their results indicated that under high-humidity conditions, the degree of surface oxidation increases with temperature. The formation of iron hydroxides increases friction and accelerates surface damage. With increasing relative humidity, water content in oxide debris reaches saturation, causing the debris to become paste-like, which reduces the adhesion coefficient. Moreover, under high humidity, the plastic deformation layer on the wheel surface becomes thicker, and both the depth and length of cracks exceed those observed under medium and low humidity conditions. Li et al. [81] selected widely used 316L and 420 stainless steel alloy powders as cladding materials and designed three environmental conditions based on temperature and humidity variations across different regions in China (25 °C-60% RH, 50 °C-60% RH, and 50 °C-90% RH). Through friction and wear tests, they evaluated the performance of wheels repaired by laser cladding under these conditions. The results demonstrated that wheels repaired using 316L stainless steel powder exhibited superior tribological performance.

Overall, current studies have identified the key mechanisms governing wheel material behaviour in low temperature environments, particularly the coupled effects of adhesion

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behaviour, plastic deformation, microstructural evolution, and brittle fracture. Despite such progress, a systematic understanding of multivariable coupling and long-term service behaviour under extreme low temperature conditions remains insufficient. In hot and humid environments, degradation is dominated by tribochemical effects, but existing research still focuses on isolated environmental factors. As a result, the coupled influences of multiple fields and the long-term evolution of corrosion and fatigue damage remain inadequately understood.

3. In-service degradation and life prediction

Wheel-rail contact governs the transfer of traction and braking forces, wheelset guidance, and the dynamic stability margin of railway vehicles, making it a core issue in railway safety and durability. Wear and surface damage at the wheel-rail interface are not only material degradation problems, but also manifestations of evolving contact mechanics under repeated rolling, creepage, impact, and changing profile geometry. Over many years, rig based and full-scale tests have been widely used to investigate whether higher wheel and rail hardness can mitigate rapid wear and delay surface-initiated damage, and to determine how wheel–rail hardness matching affects service life at the system level. When wear becomes severe, or when spalling and polygonal wear develop, deterioration in ride quality, increased vibration and impact loading, and accelerated damage to both wheels and rails may follow. Accurate prediction of wear and profile evolution is therefore a prerequisite for effective reprofiling and renewal decisions, and is central to wheelset life extension, life cycle cost reduction, and the maintenance of stable operating quality.

3.1 Wheel-rail material matching, hardness ratio and wear response

To improve wheel-rail wear performance and to clarify the effect of material pairing on wheel wear resistance, extensive experimental investigations have been carried out using wheel-rail test rigs, as shown in Fig. 7. These studies indicate that the wheel–rail hardness ratio has a significant influence on the wear behaviour of both wheels and rails, with localised fatigue related wear generally emerging as the dominant damage mode. Maintaining the hardness ratio within an appropriate range is therefore essential for optimising wheel–rail wear performance and ensuring safe train operation.

Figure 7 Wheel-rail interaction test rig

Conventional studies held that increasing the hardness of one material reduces its own wear but aggravates the wear of the mating material [82]-]83], indicating a typical trade-off in wheel-rail wear. However, full-scale tests conducted by Stock et al. [84] and Heyder et al. [85] showed that increasing rail hardness did not increase wheel wear; under some matching conditions, wheel wear even decreased. Zhao et al. [86] studied similar findings, namely that increasing rail hardness reduced rail wear, while wheel wear changed only slightly. To explain these discrepancies, researchers proposed that the wheel–rail hardness ratio may be the key parameter governing wear behavior and subsequently carried out systematic studies to reveal its regulatory mechanism. Hu et al. [87] investigated multiple cross-matched combinations of wheel and rail materials and found that wheel wear rate decreases with increasing wheel hardness. Under certain creepage and contact-pressure conditions, rail wear was also correlated with wheel hardness. Meanwhile, the overall wear rates of the wheel-rail system increased with increasing wheel/rail hardness ratio, indicating that hardness matching has a pronounced effect on wear behavior. Wang et al. [88] showed that, with increasing wheel hardness, wheel wear decreases whereas rail wear increases, and the total wheel–rail wear first decreases and then increases, reaching a minimum when the wheel and rail hardness are approximately matched. At the same time, the dominant damage mode shifts from pitting and spalling at lower hardness to large-scale spalling at higher hardness, while rail damage evolves from slight spalling to deeper subsurface spalling. These results further indicate that, as the wheel/rail hardness ratio increases, wheel wear decreases and rail wear increases, and that the total wear reaches an optimum when the hardnesses are properly matched. It provides a quantitative basis for understanding the influence of hardness ratio on wear partitioning and service performance. Hu et al. [89] further investigated the effects of varying wheel-rail hardness ratio on wear and rolling contact fatigue (RCF) behavior. Their results showed that when the wheel/rail hardness ratio (Hw/Hr) increased from 0.927 to 1.218, the wheel wear rate decreased, with the most pronounced reduction occurring at Hw/Hr=1.218, whereas the rail wear rate increased. Zhang et al. [90] studied wheel-rail pairs with different hardness levels and found that when the wheel/rail hardness ratio was controlled at approximately 1.15:1, the total wear was minimised and the surface damage was the least severe. Increasing wheel hardness reduced wheel wear and suppressed polygonal wear. Chang et al. [91] evaluated nine hardness-matching combinations involving three types of wheel and rail materials. It found that when the wheel/rail hardness ratio was below 1.05, polygonal wear readily developed on the wheel specimens, whereas when it exceeded 1.36, polygonal wear was almost completely suppressed, although rail wear increased. The results indicate that the wheel–rail hardness ratio plays a decisive role in regulating wear partitioning. Ma et al. [92] evaluated the wear behavior of six rail materials paired with wheel specimens of different hardness and analysed wear debris morphology, microhardness, and contact fatigue performance. Th results showed that when the rail/wheel hardness ratio (Hr/Hw) was below 0.96, rail wear increased; when Hr/Hw exceeded 1, the rail wear rate remained at a relatively low level, and when Hr/Hw exceeded 1.25, rail wear decreased sharply. In contrast, wheel wear shown that the opposite trend, increasing when Hr/Hw reached 1.28.

Overall, current studies indicate that maintaining the wheel-rail hardness ratio within approximately 1.0 to 1.2 is beneficial for reducing wear and mitigating damage, thereby improving the overall service performance of the wheel-rail system. Control of the wheel-rail hardness ratio has thus become a key approach to improving wear resistance and service reliability. However, although the basic relationships among hardness ratio, wear partition, and damage evolution have been built, the coupled influences of contact stress, creepage, and material microstructure under

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complex operating conditions remain to be clarified. Addressing these issues will be essential for translating current understanding into practical wheel-rail design and maintenance strategies.

3.2 Wheel wear prediction and profile evolution

Wheel wear prediction is generally formulated as a profile evolution problem for the tread and flange under representative operating conditions. In a typical simulation framework, a virtual operating environment is first designed by specifying route geometry and irregularities, vehicle speed history, traction and braking conditions, wheel–rail contact states, and material properties. The vehicle-track system response is then computed to obtain contact forces, creepages, and contact patch kinematics, which are subsequently linked to a wear law to estimate local material removal and update the wheel profile over a reprofiling interval. Most mechanism-based approaches are therefore built on the coupling of three essential modules, namely a vehicle-track dynamic model, a wheel-rail contact model for normal and tangential interaction, and a wear calculation module with profile updating and smoothing procedures. In parallel, data driven approaches have been developed from measured profile histories and wear related indicators using numerical analysis, regression methods, and machine learning techniques. Such approaches are increasingly used to accelerate prediction, improve computational efficiency, and compensate for model bias associated with fleet variability and operational uncertainty.

3.2.1 Mechanism-based wear modelling

Numerous physical-driven models have been developed for wheel wear prediction. Pearce and Sherratt [93] proposed a simplified cyclic calculation model in which the wear distribution along the wheel profile is predicted by accumulating wheel–rail contact positions, creep forces, and creepages. Bevan et al. [94] developed a damage model based on route operating spectra, in which parameters such as curve radius, cant, and traction/braking conditions were incorporated into dynamic simulations to achieve coupled prediction of tread wear and rolling contact fatigue (RCF). Wang et al. [95] used an integrated model coupling wheel wear with vehicle dynamics. By considering nonlinear factors in the traction transmission system, the model was able to analyse the wear differences between motor and trailer cars, and its accuracy was validated against field measurements. Chang et al. [96] constructed a three-dimensional dynamic finite element model in Abaqus and combined it with the Archard wear law to predict wheel-rail rolling contact wear. Zeng et al. [97] coupled a vehicle dynamics model with the Archard model to reveal the evolution of wheel wear under acceleration conditions. Braghin et al. [98] combined multibody dynamics with the FASTSIM algorithm, achieving relatively high accuracy in tread wear prediction. To assess the applicability of different modelling approaches, many comparative studies have also been carried out. Wang [99] analysed several signal-processing methods and pointed out that Fourier transform and moving average methods are more advantageous for polygonal wear prediction. Niu et al. [100] compared Hertzian and semi-Hertzian contact algorithms and found that the semi-Hertzian model is closer to actual behavior in long-term wear prediction. Further studies have shown that different contact models can influence prediction results. Tao et al. [101] reported that the Hertz+FASTSIM combination provides a good balance between computational efficiency and accuracy. Yang et al. [102] showed that non-Hertzian models offer higher accuracy but at greater computational cost, whereas Hertzian models are more suitable for long-term engineering applications of wear prediction. Overall, physical wheel wear prediction models have evolved from simplified empirical formulations to refined multiphysics coupled models.

Current studies show that mechanism-based wear prediction can reproduce tread and flange profile evolution when route spectrum, operating states, contact algorithms, and profile update rules are specified consistently, and validation against twin-disc or field measurements is essential to demonstrate credibility. The key risk is that long-distance prediction is sensitive to modelling choices that are often treated as technical details, including contact formulation (Hertz versus non-Hertz), tangential algorithm, smoothing strategy, and the representation of traction, braking, and variable friction; these choices can shift predicted wear migration and flange involvement. Mechanism-based workflows can therefore be configured around the intended application, using computationally efficient contact models for fleet-level studies when justified, and reserving higher-fidelity contact or FE formulations for regimes where stress distribution, plasticity, and local damage mechanisms govern wear evolution.

3.2.2 Data-driven wear modelling

To address the limitations of conventional vehicle-dynamics-based models, particularly their high computational cost and limited generalizability, researchers have turned to data-driven approaches for wheel wear prediction. Early methods mainly relied on statistical models to fit and extrapolate historical data. Zhu et al. [103] employed polynomial functions based on operational data to predict wheel wear, while Costa et al. [104] combined inspection data with a Markov decision process (MDP) to construct prediction models for wear rate and service life. Although these methods are straightforward to implement, they are highly dependent on data quality and quantity, provide limited insight into complex underlying mechanisms, and often show insufficient long-term predictive accuracy. On this basis, machine-learning-based methods were gradually introduced. Chi et al. [105] employed a Bayesian model to predict polygonal wear, improving model flexibility, although the approach remained constrained by data scale and generalisation capability. Iwnicki [106] developed a neural-network-based model with exogenous inputs for wheel-rail wear prediction. Deng et al. [107] combined a nonlinear autoregressive neural network with exogenous inputs (NARNN), the Levenberg-Marquardt (LM) algorithm, and orthogonal matching pursuit (OMP), improving both prediction accuracy and model compactness. In recent years, deep learning and data augmentation techniques have further advanced this field. Shangguan et al. [108] used TimeGAN to generate wear data and combined it with a gated recurrent unit (GRU) network for state prediction, alleviating the problem of insufficient data. Liu et al. [109] proposed a two-step prediction framework based on DBSCAN and multi-model fusion, enabling coordinated prediction of both fleet-level and single-wheel wear. In this framework, the GA-BPNN and LSTM models achieved the best performance in overall and individual prediction tasks, respectively.

Existing work indicates that data driven methods can deliver rapid wear prediction and capture fleet variability when trained on representative inspection and monitoring datasets. Nevertheless, their generalisability may deteriorate when operating regimes, friction conditions, or maintenance practices differ from those represented in the training data. In addition, sensitivity to data quality, measurement consistency, and latent covariates can introduce prediction drift and confident remaining life estimates. Data driven wear prediction is therefore most credible when operating state descriptors are incorporated, predictive uncertainty is quantified, and model calibration is constrained by physics-based knowledge.

3.2.3 Hybrid frameworks for wear and RCF prediction

Both mechanism based and data driven approaches show clear limitations when used independently. Mechanism based models are often

demanding and sensitive to the selection of contact algorithms and wear coefficients, whereas purely data driven models may have limited transferability across routes and operating regimes and often lack physical interpretability. For this reason, hybrid frameworks have been proposed to combine physics-based structure with data driven calibration or correction, as shown in Fig. 8, with the aim of improving prediction robustness and capturing the closed loop evolution of wheel wear over successive reprofiling cycles.

Zeng et al. [125] introduced a physics-data dual-driven framework that couples wear evolution with reprofiling by integrating multi-location wear characteristics and reprofiling behaviour within a closed-loop model. Numerical prediction was used to estimate wear state and assess remaining useful life, and the framework was reported to provide reliable prediction accuracy with practical application in wheel wear prediction and health management. Wang et al. [126] proposed a hybrid strategy in which a physics-based model first estimates degradation rates under representative operating conditions, and a data-driven model then evaluates wheelset life cycle using reprofiling removal at the flange, predicted or measured wear indicators, and operational reprofiling requirements. Outputs were used to determine maximum service life under safety regulations and operator performance criteria, with reported agreement against operational data from high-speed services. Zhu et al. [127] proposed a combined Physical model and data-driven method that uses least squares regression to quantify discrepancies between measured and simulated wear at fixed mileage intervals and to calibrate the Jendel wear model. By integrating vehicle dynamics, wheel-rail contact modelling, and the calibrated wear model, metro wheel wear was predicted over additional mileage; improved accuracy and reduced dependence on empirically chosen wear coefficients were reported. Hartwich et al. [128] proposed a hybrid concept for wheel profile prediction that combines a dynamics model based on wheel-rail contact theory with post-processing of measurement data.

Hybrid methods also motivate practical criteria for coordinating wear and RCF risk within maintenance decisions. When prediction outputs are used to schedule reprofiling, the relevant decision variable is not wear depth alone but the combined evolution of profile geometry (affecting equivalent conicity and dynamics response) and damage accumulation (affecting RCF risk). Hybrid frameworks that embed reprofiling cycles therefore provide a natural route to define consistent intervention thresholds and to update remaining-life

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estimates as measured profiles and condition indicators become available.

The literature indicates that hybrid frameworks improve wear prediction credibility by calibrating wear coefficients and operating-state dependence against measurement data while retaining physics-based structure for extrapolation across mileage and reprofiling cycles. The key risk is that calibration can compensate for unmodelled mechanisms, such as friction variability, thermal history, and damage-mode transitions between wear and RCF, which can reduce robustness when conditions change. Hybrid prediction can therefore be implemented within a closed-loop maintenance framework in which operating descriptors, monitoring indicators, and intervention rules are aligned, and where model updating and uncertainty treatment are explicit.

Physics-based models are well suited for elucidating wheel-rail contact mechanisms and conducting parametric sensitivity analyses; however, the engineering deployment requires careful consideration of computational cost and parameter availability. Data-driven models, by contrast, are advantageous for online updating and rapid prediction, although their transferability across different lines and robustness under operating condition drift necessitate appropriate calibration strategies. Hybrid approaches that combine physics-based and data-driven paradigms are more suitable for closed-loop maintenance scenarios, where physical constraints can be leveraged to improve generalisation capability, while data assimilation can be employed to mitigate long-term prediction bias.

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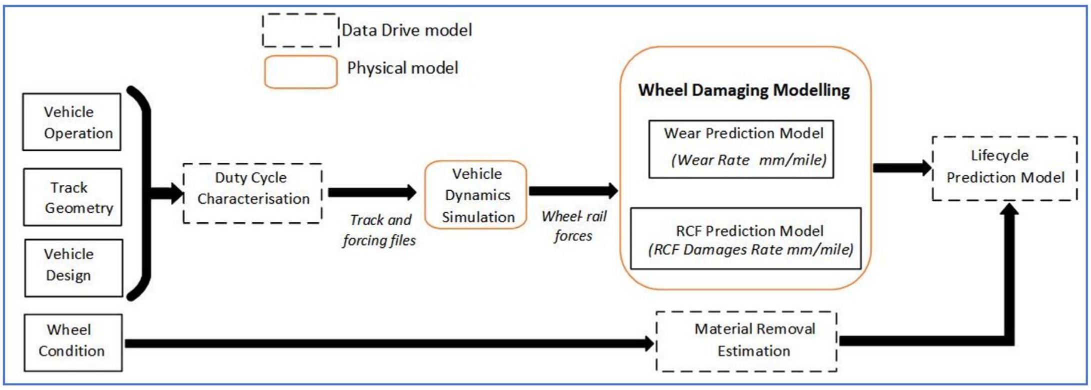

Figure 8 Hybrid framework based on physics and data-driven models

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3.3 Rolling contact fatigue assessment under wheel-rail loading

With the transition of wheel-rail systems from wear dominated behaviour to coupled multi damage mechanisms, remaining useful life (RUL) assessment has become considerably more complex. International research has therefore placed increasing emphasis on rolling contact fatigue crack propagation, the competing effects of wear and spalling, and probabilistic remaining useful life prediction. As a result, an integrated assessment framework combining physics-based models with statistical methods has gradually been developed. Johnson investigated RCF damage under both point and line contact conditions and proposed corresponding shakedown map criteria [115]-[116], which have become one of the most widely used core methods for predicting wheel RCF. Johnson [117] initially developed the shakedown map based on full sliding conditions, which was later extended to rolling–sliding conditions by Bower et al. [118]. This method qualitatively describes and evaluates the material response of wheel–rail systems under three parameters: maximum contact stress P_0, material shear yield strength k, and friction coefficient μ. Within the shakedown map framework, the horizontal shortest distance from the operating point to the ratcheting boundary is defined as the fatigue index (FI) for wheel-rail surface crack prediction. This fatigue index is related to the initiation and propagation of surface fatigue cracks and is closely associated with spalling and flaking processes, which constitute severe and sudden wear mechanisms. A series of twin-disc experimental data indicate that, regardless of variations in normal load, the wear rate shows an exponential relationship with the fatigue index. Furthermore, when the fatigue index approaches zero, it signifies the onset of severe wear. Some researchers have proposed that the fatigue index, derived from shakedown theory and used to predict surface-initiated fatigue in railway wheels, can serve as a key parameter for evaluating rolling contact wear rate [119]. However, other studies have shown that under high creepage conditions, the predictive capability of the fatigue index for fatigue damage decreases [120]. Analysis based solely on the shakedown map has inherent limitations, as it does not account for the influence of material wear on RCF during rolling friction processes. Therefore, in addition to shakedown theory, it is necessary to combine other predictive approaches, such as damage functions, to systematically investigate fatigue damage behavior. Rolling contact simulation experiments have introduced the concept of dissipated energy per unit contact area, $T\gamma/A$, which has been shown to correlate with wear rate per unit length or contact area [121]. Based on this finding, new damage function models have been developed for wheel fatigue damage and wear, enabling the prediction of both fatigue crack propagation and wear rate. Butini et al. [122] developed a coupled model integrating wear and RCF, allowing simultaneous prediction of wheel-rail profile evolution and the accumulation of surface RCF damage. Dong [123] conducted thermo-mechanical coupled simulations to analyse the stress evolution of wheel treads during emergency braking of heavy-haul trains and predicted fatigue crack initiation life under different axle loads and brake shoe pressures. Mazzù and Donzella [124] proposed a predictive model based on steady-state strain fields derived from integral equations, considering shear stress and plastic strain increments along the depth direction, which can predict crack morphology under high-cycle loading conditions. Zhou et al. [125] developed a three-dimensional finite element model of wheel-rail contact incorporating vertical cracks, revealing the competitive relationship between wear and fatigue crack propagation under rolling-sliding conditions. Regarding crack propagation and life prediction, Zhang et al. [126] analysed the effects of wheel-rail dynamic characteristics, complex operating conditions, and surface defects on RCF crack initiation, and proposed a corresponding prediction framework. Arana et al. [127] developed an RCF prediction approach that integrates crack initiation, crack propagation, and nonlinear multibody dynamics, enabling the prediction of RCF behavior across different track sections.

The literature indicates that shakedown-based stability diagrams and derived indices provide practical screening tools for surface-initiated RCF risk, while dissipated-energy damage functions and coupled wear-RCF models offer a route for joint assessment of wear and fatigue evolution. Predictive robustness depends on representation of near-surface state change, friction variability and thermal history, and therefore requires validation against rig and field observations under representative operating spectra.

Table 3 Comparison of representative modelling approaches for wheel-rail wear and RCF assessment

Domain	Method Type	Key Inputs / Data Requirements	Key Outputs / Indicators	Main Features and Applicability Boundaries
Wear	Physics-based	Contact parameters, creepage, material properties, and operating conditions	Wear amount, profile evolution	High interpretability; sensitive to input parameters and computationally expensive; suitable for mechanism investigation and comparative assessment of schemes
Wear	Data-driven	Historical inspection data, operational data, and extracted features	Wear/life trends, RUL	Easy to update online; subject to transferability limitations and condition-drift risks; suitable for lines with sufficient data
Wear	Hybrid physics–data-driven	Physics-based prior constraints combined with data updating	Wear/RUL with uncertainty	Balances predictive accuracy and interpretability; complex framework construction; suitable for closed-loop operation and maintenance
RCF	Shakedown map / fatigue index	Contact stress and material parameters	Risk zoning/thresholds, FI, etc.	Intuitive classification; limited capability in describing damage evolution and coupling effects; suitable for preliminary screening and early warning
RCF	Damage function / accumulation model	Creepage, load spectrum, and calibration parameters	Damage accumulation / risk	Convenient for coupling with wear models; dependent on calibration quality; suitable for line-level assessment
RCF	Experimentally calibrated model	Experimental data, material parameters, and process parameters	Life / crack-related parameters	Effective for comparing materials and manufacturing processes; limited extrapolation capability; suitable for process validation

4. Condition monitoring and maintenance interventions

As railway systems move towards higher speed, heavier axle load, and greater asset utilisation, wheel damage prediction, maintenance planning, and performance restoration have become central to both running safety and whole life cost control. In parallel with network expansion, maintenance practice is increasingly shifting from fixed time or mileage-based scheduling to condition based maintenance. The effectiveness of such a transition depends on the integration of three interrelated functions: accurate condition monitoring and defect diagnosis, intervention planning that balances safety margin against material removal, and restoration or strengthening technologies that recover surface integrity and suppress recurrent damage.

This section considers wheel maintenance as a closed loop process comprising condition monitoring and defect detection, decision making and intervention planning, and reprofiling, repair, and surface reinforcement. Emphasis is placed on the translation of monitoring indicators and prediction outputs into intervention thresholds, and on the feedback of intervention outcomes into subsequent assessment and trigger logic. The objective is to clarify technically defensible routes for wheelset condition-based maintenance, covering depot based and in service monitoring, cost effective turning and reprofiling strategies, and restoration technologies including laser cladding and surface strengthening.

4.1 Condition monitoring and defect detection

Timely and reliable detection of wheel tread defects is fundamental to the control of vibration excitation, ride quality deterioration, and in service safety margin. In engineering practice, wheel condition assessment relies on two complementary pathways, namely depot-based inspection, which offers higher measurement fidelity under controlled conditions, and in service monitoring, which supports earlier defect detection and interim risk control through wayside and on-board systems. More recently, data driven diagnosis has become an increasingly important decision support tool, improving defect recognition, localisation, and severity classification through large scale inspection and monitoring datasets, while facilitating more consistent condition indicators and maintenance trigger criteria across fleets and operating environments [128].

4.1.1 Depot-based inspection

Depot-based inspection is performed when vehicles are parked and, in some cases, may require wheelset disassembly. Such procedures can be labour intensive and time consuming, and may constrain depot throughput and availability. Traditional manual inspection often relies on operator judgement using hammering, auditory cues, and basic gauges. Although widely used because of low equipment cost, manual inspection is limited by measurement resolution and repeatability, and is prone to missed detection and false calls for certain defect types.

Development of optoelectronic measurement and sensor technology has enabled more instrumented depot inspection. Contact and non-contact systems using lasers and dedicated sensors can scan wheel profiles and evaluate tread geometry from measured data, reducing operator dependence and improving repeatability. Early examples include rapid tread wear and geometric deviation measurement systems developed in the United States and wheelset dimensional inspection devices developed in Japan for in-service wheelsets. In China, substantial progress has been reported for detection of tread surface and near-surface damage using electromagnetic ultrasonic techniques based on controlled excitation and reception mechanisms [129]-[130]. Given the maturity and broad coverage of depot-based inspection in the literature and standards, detailed discussion is not expanded further in this review, and emphasis is placed on in-service detection and intelligent diagnosis in the following subsections.

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4.1.2 Wayside and on-board monitoring

Wayside and on-board monitoring enables wheel condition assessment without stopping the vehicle, supporting rapid inspection with a high level of automation. Such dynamic approaches can provide earlier defect detection than depot-only inspection and can reduce the risk of defect growth between maintenance intervals (Fig 8). Current practice is dominated by three technical routes: vision-based inspection, ultrasonic inspection (including EMAT and laser-ultrasonic variants), and vibration-based monitoring. Increasingly, current sensing approaches are combined with data-driven diagnosis to improve defect recognition, localisation, and severity assessment in operational environments.

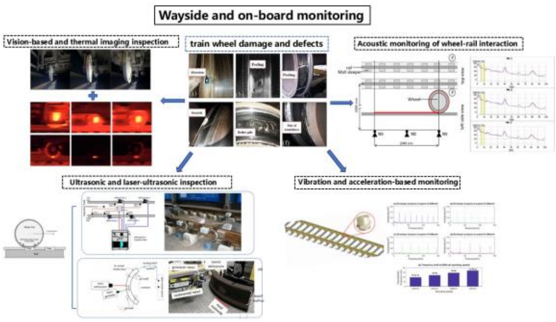

Figure 8 Wheel wayside and on-board monitoring [135]-[146].

(1) Vision- and thermography-based inspection techniques

Visual image-based inspection of railway wheel treads is a non-contact online/offline detection approach that integrates machine vision, digital image processing, and artificial intelligence, with current developments being primarily driven by deep learning. At an early stage, Japan, the United States, and Germany each developed automatic wheel inspection systems based on image processing and sensing technologies, enabling tread parameter measurement and wear assessment under different operating speeds [131]-[132]. Zhao et al. [133] developed a system for wheel tread defect recognition and detection, and investigated image region extraction techniques for the inspection process. Wu Kaihua et al. [134] employed laser scanning to acquire wheel tread wear images, from which the wear condition was determined through subsequent analysis and processing. During the machine-learning stage, Deilamsalehy et al. [135]-[136] achieved high-accuracy wheel defect detection under thermographic imaging conditions by combining histogram of oriented gradients (HOG) features with a support vector machine (SVM) classifier, with a recognition rate of 98%. In recent years, deep learning methods have become a major research focus. Shaikh et al. [137] constructed the FaultSeg dataset to support the training of deep learning models for wheel damage detection. Xing et al. [138] developed a model for railway wheel surface defect detection that enables the classification and identification of four types of wheel tread defects. Trilla et al. [139] proposed a deep learning-driven method for the automatic detection and classification of wheel tread defects, in which a convolutional neural network (CNN) was used to integrate defect recognition, size prediction, and localisation. Emoto et al. [140] further improved inspection performance by combining laser sensing and vision-based techniques with artificial intelligence models.

(2) Acoustic detection techniques based on wheel-rail interaction

Acoustic detection identifies damage by acquiring wheel–rail contact noise or vibration signals. Germany and the United States have developed online inspection devices based on ultrasonic and acoustic technologies. Komorski et al. [141]-[142] collected wheel-rail noise signals using a wayside multi-microphone array and identified wheel damage through joint time–frequency analysis (JTFA). They further combined Fourier transform and Hilbert transform for vibro-acoustic diagnosis and proposed a monitoring method for wheel tread flats, thereby enabling non-contact dynamic inspection.

(3) Ultrasonic and laser-ultrasonic inspection techniques

Ultrasonic inspection techniques can be used to identify internal and near-surface wheel defects. Salzburger et al. [143] proposed the AUROPA III system based on electromagnetic acoustic transducers (EMATs), which enables non-contact inspection at speeds of up to 15 km/h and can rapidly complete screening of an entire train. Montinaro et al. [144] proposed an unconventional non-contact laser-ultrasonic approach for railway wheel inspection. This method uses a laser interferometer to receive ultrasonic waves in a non-contact manner, and the receiving system allows flexible selection of the distance between the inspection surface and the interferometer, thereby overcoming spatial accessibility constraints. Cavuto et al. [145] further advanced laser-ultrasonic inspection technology by achieving fully non-contact inspection through laser excitation and interferometric measurement. By additionally incorporating a finite element model to optimise the inspection procedure, the method offers high inspection efficiency, strong flexibility, and non-destructive testing capability.

(4) Wheel damage detection methods based on vibration acceleration

Vibration acceleration-based detection methods identify wheel damage by measuring impact signals generated during wheel-rail contact. These methods are characterised by simple instrumentation and strong adaptability, and have already been applied in countries such as Russia and Japan. Wang et al. [146] developed a vehicle-track coupled dynamic model with 73 degrees of freedom and, by combining time-frequency analysis and wavelet transform, extracted features from axle-box vibration signals to achieve accurate identification of wheel tread flats in high-speed trains.

4.1.3 Multimodal sensor fusion for robust wheel condition assessment

Although vision based, ultrasonic, acoustic, and vibration-based approaches are often discussed separately, multimodal sensor fusion is playing an important role in practical wheel condition monitoring. In complex railway environments, the performance of a single sensing modality may deteriorate substantially owing to variations in illumination, interference from rain and snow, aerodynamic noise, surface contaminants, installation constraints, and differences in track excitation. To address the limited robustness of single modality sensing under such demanding operating conditions, increasing research attention has been directed towards heterogeneous sensor fusion techniques for accurate fault identification in railway vehicles [147].

Existing studies have implemented fusion at three levels, namely data level, feature level, and decision level. At the data level, Deng et al. [148] transformed multisource signals into a unified image representation using the symmetric dot pattern method, thereby achieving raw data fusion. Combined with deep neural networks for fused feature extraction and improvement, the proposed approach demonstrated superior accuracy and noise robustness compared with both single source and conventional multisource models on public and noise augmented datasets. Wang et al. [149] directly fused vibration and acoustic signals by combining a grey wolf optimiser with a support vector machine for rapid fault identification, further confirming the effectiveness of heterogeneous acoustic and vibration inputs in improving both detection efficiency and diagnostic accuracy.

At the feature level, Makrouf et al. [150] proposed a transfer learning-based framework for the fusion of vibration and acoustic features. In that method, continuous wavelet transform was first used to generate multi-sensor time frequency representations, after which the fused wavelet coefficients were employed to fine tune a pretrained convolutional neural network. The resulting method achieved better diagnostic performance than single modality approaches under variable speed and compound fault conditions. Deng et al. [151] further developed an improved RSMamba network based on multidomain image fusion, in which time domain, frequency domain, and time frequency domain features were encoded, while attention mechanisms were introduced to strengthen the identification of critical features. Such studies indicate that feature level fusion can make fuller use of the complementary information provided by different sensing modalities and feature domains, and has become one of the most representative routes in heterogeneous sensor fusion based fault diagnosis.

At the decision level, Mey et al. [152] adopted a stepwise fusion strategy to integrate the diagnostic outputs of vibration and acoustic emission sensors, thereby combining low frequency vibration information with high frequency acoustic emission information to improve the classification accuracy of incipient damage. Compared with data level and feature level fusion, decision level fusion does not require strict synchronisation of raw data and offers better fault tolerance when a single sensing channel fails or its signal quality deteriorates. Such characteristics make it more suitable for online deployment in complex engineering environments.

Overall, heterogeneous sensor fusion can be implemented at the data, feature, and decision levels, corresponding respectively to joint representation of raw measurements, complementary improvement of multimodal features, and integration of independent diagnostic outputs or health indicators. Compared with single modality monitoring, multimodal fusion offers greater diagnostic robustness, lower false alarm rates, and more reliable assessment of damage severity for condition-based maintenance. More importantly, static inspection, dynamic monitoring, and heterogeneous sensor fusion can be viewed as complementary components of an integrated wheel condition assessment framework. Static inspection provides high accuracy for condition confirmation and maintenance verification, dynamic monitoring supports early warning and continuous in-service tracking, and heterogeneous sensor fusion improves diagnostic reliability under complex environments and variable operating conditions.

4.1.4 Data augmentation and small-sample learning for rare abnormal states

To address data scarcity in rare anomalous states, existing studies have focused on two routes for improving the generalisation capability and robustness of mechanical fault diagnosis models, namely data augmentation and few shot learning.

Table 4. Comparison of three diagnostic and monitoring paradigms for wheel/wheelset damage

Comparison Dimension	Static Inspection Technologies	Dynamic Monitoring Technologies	Heterogeneous Sensor Data Fusion Technologies
Typical sensing means	Manual inspection, gauges, laser profile measurement, dedicated NDT devices, EMAT, etc.	Wayside vision, thermography, acoustic arrays, onboard/wayside vibration, laser ultrasonics, etc.	Multimodal combinations such as vibration + acoustics, vibration + acoustic emission, vibration + thermography, vision + laser, and ultrasound + vibration
Data acquisition mode	Intermittent, offline, and pointwise inspection	Continuous or periodic online acquisition covering the operating process	Synchronous or quasi-synchronous multisource acquisition, or late fusion of outputs from independent models
Main strengths	Stable inspection conditions, high signal-to-noise ratio, high accuracy, and good repeatability; suitable for quantitative defect and geometry assessment	No need for service interruption; enables automation, frequent monitoring, and early warning; well aligned with condition-based maintenance	Exploits complementarity among modalities, improves robustness, reduces false alarms, and improves generalisation under complex conditions
Main limitations	Dependent on depot windows; relatively high labour and time cost; cannot cover the full-service process; early abnormalities may develop between inspections	Single sensors are vulnerable to environmental and operational disturbances, with noticeable feature drift and risks of missed or false alarms	Higher system complexity, with increased requirements for synchronisation, data quality, fusion models, and computational resources
Environmental sensitivity	Relatively low because the inspection environment is usually controllable	Relatively high; vision is affected by glare, contamination, and illumination variation, acoustics by rain/snow, aerodynamic noise, and wheel–rail noise, and vibration by track excitation and mounting paths	Reduces the risk of single-channel failure through multimodal redundancy and complementarity; the most promising route for harsh environments
Real-time capability	Low	High	Medium to high, depending on the fusion level and computational architecture
Diagnostic characteristic	“High visibility and high decision”	“Early detection and wide coverage”	“Stable decision-making, disturbance resistance, and integrated assessment”
Implementation challenges	Inspection efficiency, labour dependence, disassembly requirements, and depot throughput constraints	High-speed acquisition, field noise, sensor deployment, and shortage of labelled data	Multisource asynchrony, inconsistent sampling rates, missing data, cross-modal feature alignment, and model interpretability
Suitable scenarios	Depot precision inspection, verification, wheelset withdrawal decisions, and post-maintenance acceptance	Wayside online screening, onboard continuous monitoring, and abnormality warning	Robust diagnosis in high-speed, noisy, harsh-weather, and high-reliability applications
Relationship with CBM	Provides high-confidence condition references and maintenance threshold support	Provides condition tracking and early warning between depot inspections	Provides more reliable health indicators and severity assessment, making it more suitable for CBM triggering
evaluation	A high-accuracy benchmark inspection approach, but unable to provide full-process perception	The most important engineering route for online monitoring, but limited by the robustness of single modalities	A key future direction for intelligent wheel/wheelset PHM, especially for reliable diagnosis under complex environments

Wright et al. [153] noted that conventional deep learning methods often depend on signal sampling over specific cycles or fixed time intervals, making the resulting models sensitive to sampling strategies and previously unseen operating conditions. To mitigate this limitation, they used a sliding window technique to augment phase current signals, thereby reducing the bias associated with insufficient training sample coverage and improving both classification accuracy and cross condition generalisation. In rolling bearing fault diagnosis, where model construction is often complicated and adaptability to different input forms is limited, related efforts have also increasingly explored more flexible strategies for improving model transferability and

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robustness. Wang et al. [154] proposed a general diagnostic framework based on AlexNet. In their method, raw vibration signals were transformed into fixed-size time-frequency images, and multiple time-frequency analysis techniques were employed to generate standardised inputs, thereby reducing the difficulty of model design and providing a feasible pathway for unified feature representation under few-shot conditions. Furthermore, to address the shortage of fault samples and pronounced distribution shift in railway mechanical systems under varying operating conditions, Shi et al. [155] combined multibody dynamics simulation with fast weighted feature space averaging to develop a data augmentation framework integrating physical priors with feature improvement. This approach not only generates simulated fault samples that more closely approximate real-world data, but can also be embedded into transfer learning workflows, thereby improving model robustness under scarce fault data and varying operating conditions. From the perspective of generative modelling, Ma et al. [156] proposed a sparse-constrained generative adversarial network (SC-GAN), which enables stable generation of raw vibration signals through autoencoder pretraining, sparse regularisation, and a two-stage training strategy. This method effectively expands samples of rare fault states and improves diagnostic accuracy and cross-device generalisation in both rolling bearing and gearbox applications. Meanwhile, from the perspective of few-shot learning, Che et al. [157] proposed an ensemble meta-learning (EML) model, in which high-dimensional vibration signals were converted into grayscale images, meta-learning tasks were constructed, and multiple meta-learning sub-models were integrated, enabling rapid adaptation and accurate identification under few-sample and varying-condition scenarios.

Overall, above mentioned studies indicate that data augmentation can improve the recognition of rare faults by enriching the sample distribution, whereas few shot learning and meta learning can improve transferability and adaptability across operating conditions and diagnostic tasks when labelled data are limited. These approaches are emerging as important technical routes for addressing anomalous sample scarcity in intelligent fault diagnosis.

4.1.5 Advanced weak-feature extraction under harsh operational environments

Under high speed and heavy haul operating conditions, the vibration response of wheels and wheelset systems is impacted by multiple coupled factors, including wheel-rail excitation, track irregularities, speed variation, and environmental noise, with the result that weak fault signatures are readily obscured. Conventional methods, such as Fourier transform and wavelet analysis, are effective for describing frequency domain and time frequency characteristics, but remain limited in extracting incipient damage features under strongly nonlinear, non-stationary, and low signal to noise ratio conditions. Advanced signal processing and intelligent identification methods have therefore attracted increasing attention as means of improving the accuracy and robustness of wheel and wheelset damage diagnosis.

Wang et al. [158] proposed a dynamic wheel polygonisation detection method based on the iterative corrected discrete Fourier transform, which can reduce the influence of speed variation and track irregularities on detection results. To address the non-stationary characteristics of wheel vibration responses, Chen et al. [159] achieved quantitative detection of wheel polygonal wear under variable-speed conditions using an adaptive chirp mode decomposition method. For the recognition of tread damage images, He et al. [160] designed a hybrid convolutional encoding architecture for typical wheel defects, including wear, spalling, flats, and cracks, in order to enlarge the network receptive field while preserving detailed features. In addition, a cross-attention module was incorporated to suppress noise and redundant information, thereby improving the recognition accuracy of tread defects. Liu et al. [161] employed a field-validated three-dimensional vehicle-track coupled dynamic model and, in combination with the VMD-ES method, extracted weak features of wheel flat defects under different speeds and track irregularity conditions. The results showed that this method can extract the impact characteristics of wheel flats and achieve quantitative identification of small-sized flat defects, while still maintaining good recognition capability under the coexistence of flats and eccentricity. To address the problem that fault-related components in axle-box bearing signals are easily disturbed by track excitation and random noise, Jin et al. [162] proposed a fault diagnosis method based on parameter-optimised variational mode decomposition and an improved deep belief network, which improved fault feature extraction capability. Furthermore, Wang et al. [163] developed a reinforcement learning-based neural architecture search method that can update network structural parameters and has shown considerable potential in bearing fault diagnosis.

In summary, signal processing methods for wheel and wheelset damage diagnosis are evolving from traditional single frequency domain analysis towards adaptive decomposition, weak impact improvement, deep feature learning, and intelligent structural optimisation. Existing studies have shown that these methods offer clear advantages in suppressing complex wheel-rail background interference, improving weak fault signatures, and accommodating variable speed and non-stationary operating conditions, thereby providing more effective technical support for the early identification of train faults. Nevertheless, current research remains focused on specific defect types or laboratory scale conditions. Future work can therefore place greater emphasis on systematic investigation under complex in service line environments, multi defect coupled scenarios, and cross condition generalisation. Condition monitoring can support maintenance decision making only when measured signals are converted into interpretable condition indicators and linked to actionable thresholds. In practical application, the decision chain can include signal acquisition, feature extraction, defect and severity inference, threshold comparison, and intervention selection. Different indicators may support different maintenance actions. Profile deviation and polygonal wear metrics are closely associated with turning or reprofiling triggers, whereas crack sensitive indicators may necessitate intensified inspection, repair, or wheel withdrawal. The value of monitoring therefore lies not only in defect detection, but also in providing sufficiently robust and interpretable evidence to support the timing and selection of intervention within a condition-based maintenance framework.

Table 5 Typical wheel damage modes-observable features-detection methods-intervention measures

Damage Mode	Typical Causes / Operating Conditions	Observable Signals / Features	Common Detection Methods	Main Intervention Measures
Tread wear / profile evolution	Curve negotiation, adhesion variation, braking, etc.	Tread profile, equivalent conicity, wheel diameter difference	Profile measurement / online geometric inspection	Reprofiling; profile design and adaptation to operating conditions
RCF (surface / subsurface)	High contact stress, creepage, and load spectrum	Crack-related features, fatigue risk indicators	Ultrasonic testing / eddy current testing / image-based inspection	Contact condition control; reprofiling; repair and strengthening
Polygonisation / out-of-roundness	Resonance excitation, braking-induced heat, coupled wheel–rail excitation	Order spectrum, axle-box vibration, roundness indicators	Dynamic monitoring (vibration / imaging)	Secondary reprofiling; strategy optimisation and constraint control
White etching layer / thermal cracking	Prolonged downhill braking, thermal shock	Surface microstructural changes, thermal cracks	Visual inspection / metallographic analysis / non-destructive testing	Process and material improvement; repair and strengthening

4.2 Maintenance strategies and technologies

Maintenance practice in modern railways is increasingly shifting towards condition-based maintenance, in which monitoring outputs, predictive models, and intervention rules are coordinated to control safety risk and whole life cost. For wheelsets, effective maintenance depends on three closely connected capabilities, namely maintenance decision making and rule design, reprofiling quality and process control, and repair or reinforcement routes for restoring surface integrity. This section reviews recent progress in wheel maintenance, with particular emphasis on (i) condition-based maintenance decision frameworks and depot planning, (ii) reprofiling strategies that balance defect removal against material loss, and (iii) repair and reinforcement technologies for restoring surface integrity and delaying recurrent damage.

4.2.1 Maintenance decision-making and condition-based strategies

As railways transition from experience-based maintenance to lean condition-based maintenance (CBM), maintenance decision-making is shifting from a single safety constraint toward the coordinated optimisation of safety, cost, and efficiency. Optimisation of maintenance strategies with the objective of minimising life-cycle cost has gradually become an important research direction in wheel-rail operation and maintenance decision-making, requiring a balance between economic efficiency and reliability under safety constraints. In terms of maintenance strategy optimisation models, Liu et al. [164] proposed an interval-based maintenance strategy formulation method for multi-component systems with latent failures, in which the inspection intervals of individual components are determined by minimising the long-term operating cost rate. Vafaei et al. [165] proposed a fuzzy early-warning method based on condition-based maintenance, thereby improving diagnostic strategies within condition-based maintenance frameworks. Rahimikelarijani et al. [166] developed a railway track maintenance decision model that integrates competing failure modes and impact-driven degradation processes, and further employed Monte Carlo simulation to determine the optimal inspection intervals and intervention levels under condition-based maintenance. Erguido et al. [167] proposed a reliability-based multi-objective maintenance model and used simulation optimisation together with the NSGA-II algorithm to solve for the optimal maintenance strategy. Jiang et al. [168] developed a dynamic maintenance strategy based on condition monitoring information, aiming to minimise maintenance cost per unit time, and combined wheel diameter and flange thickness wear laws with a policy-iteration algorithm to determine the optimal reprofiling strategy. Sancho et al. [169] proposed a condition information-based optimisation method for rail maintenance decision-making, in which maintenance strategies were formulated according to indicators such as rail width, rail height, accumulated million gross tonnes (MGT), and damage state, thereby reducing rail grinding costs. Zhao [170] addressed the problems of heavy maintenance workload and insufficient efficiency in electric multiple unit depots by using an optimisation model for first-level maintenance scheduling based on flexible operation sequencing. With the objective of minimising the completion time of all trainsets, the model comprehensively considered constraints such as the number of operation lines, line capacity, and operation plans, and was solved using an improved genetic algorithm. A case study of the Taiyuan EMU depot showed that, compared with fixed operation sequencing and a single-track-position mode, flexible operation sequencing and a double-track-position maintenance mode can improve maintenance efficiency and line utilisation while shortening operation time. Wang et al. [171] pointed out that the wheel reprofiling interval is an important basis for determining vehicle maintenance cycles, and that coordinating the maintenance cycles of other components around the wheel reprofiling interval can reduce excessive maintenance.

Current studies present that CBM effectiveness depends on consistent linkage between condition indicators, prediction outputs, and decision rules, together with depot planning models that respect operational constraints. The key risk is that CBM triggers derived from incomplete indicators or unvalidated prediction models can shift maintenance burden without reducing system risk, leading to inefficient reprofiling schedules or unexpected wheel removals. Wheelset CBM can therefore be designed around the reprofiling cycle as an organising constraint, with decision logic calibrated against route-specific degradation spectra and validated using measurable outcomes such as life extension, defect recurrence rate, and depot throughput.

4.2.2 Intelligent decision-making for maintenance

To reduce the impact of prediction drift and model overconfidence on condition-based maintenance triggering, recent studies have moved beyond fixed threshold strategies towards adaptive and self-updating decision frameworks. Representative approaches include risk informed decision support, adaptive threshold setting, online model updating, incremental learning, and dynamic optimisation based on remaining useful life feedback. Consilvio et al. [166] developed a risk-based decision support system in which degradation prediction is linked to maintenance intervention once a predefined risk threshold is reached, thereby reducing both unexpected failures and redundant maintenance. Lin et al. [167] proposed an intelligent maintenance decision method that combines multidimensional degradation assessment with a stochastic degradation model accounting for flange wear, polygonal wear, and wheel–rail impact, and introduced an adaptive preventive-maintenance threshold mechanism. To address operating-condition drift, García et al. [168] incorporated online incremental classification and interpretability modules for adaptive threshold adjustment and model updating, while Martins et al. [169]

combined statistical models, clustering, hidden Markov models, and supervised learning with a "confidence sphere" mechanism to enable self-updating prediction and dynamic threshold adaptation. For dynamic multi-objective maintenance planning, Chen et al. [170] employed multi-agent reinforcement learning and used remaining useful life as feedback to continuously adjust maintenance strategy. Zhang et al. [171] further proposed a wheel maintenance strategy integrating periodic inspection and preventive maintenance, in which inspection intervals and reprofiling actions are optimised by minimising maintenance cost rate under flange-thickness-related risk constraints. Although not all of these studies were developed specifically for railway wheels, they still offer useful implications for wheel condition-based maintenance. In particular, they suggest that a robust maintenance framework can integrate prediction outputs with uncertainty and risk evaluation, online model updating, and adaptive intervention thresholds, rather than relying solely on fixed decision rules.

Overall, these studies indicate that mitigating drift and overconfidence in wheel condition-based maintenance depends not only on improved prediction models, but also on adaptive decision logic supported by uncertainty quantification, risk assessment, online updating, and threshold recalibration.

4.2.3 Wheel reprofiling strategies

Profile degradation during wheel-rail service can lead to stress concentration in the contact zone, deterioration in vehicle dynamic behaviour, and accelerated wear and rolling contact fatigue. These effects impose significant constraints on the running stability of heavy haul and urban rail vehicles and on the service life of the track system. Wheel reprofiling is therefore an essential engineering intervention for controlling wheel–rail profile matching, slowing damage evolution, and reducing operation and maintenance costs.

With respect to wheel reprofiling, Shao et al. [178] reviewed the characterisation methods, measurement approaches, and control standards for wheel polygonal wear and, based on operational data and tracking test results, summarised the basic characteristics and evolution patterns of polygonal wear in high-speed EMU wheels. On this basis, they proposed reprofiling control strategies for suppressing the development of wheel polygonisation in high-speed EMUs. Yang et al. [179] conducted a comparative analysis of the evolution of wheel out-of-round wear after machining on different lathes, and found that a wheel lathe with higher wheelset fixing stiffness can effectively suppress the development of higher-order out-of-round wear after reprofiling. Ren et al. [180] showed that when the arc length at the contact point between the wheel and the lathe driving wheel approaches an integer multiple of the wavelength of wheel polygonisation, driven-wheel-positioning reprofiling may generate a pronounced form-copying effect; they further demonstrated that adjusting the spacing between the driving wheels can improve the quality of polygon reprofiling. Huang et al. [181] proposed an optimised reprofiling strategy for controlling the wheel diameter difference of the whole vehicle based on statistical data for wheel diameter and flange wear, which can reduce the amount of material removed during locomotive reprofiling. Liu [182] presented a flange-thinning model based on the standard thin-flange tread profile and, in combination with actual wear evolution, determined an optimal tread reprofiling scheme. By incorporating the model into an economical

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maintenance framework and considering factors such as the initial turning amount and wheel diameter difference, the study optimised flange thickness, material removal, and reprofiling sequence, thereby enabling customised and refined wheel reprofiling design. Cui et al. [183], focusing on polygonal wear associated with underfloor wheel reprofiling, proposed that secondary reprofiling can effectively eliminate higher-order polygonisation. Their results further indicated that the eccentricity magnitude and phase angle of the friction roller are key factors inducing fourth-order polygonisation, that the severity of this phenomenon depends on the level of eccentricity, and that roller spacing has a significant influence on reprofiling quality.

Overall, significant progress has been made in wheel polygonisation control, reprofiling equipment development, and reprofiling parameter matching. Nevertheless, current studies remain centred on the optimisation of wheel maintenance as an isolated component, with limited consideration of the coordinated regulation between rail grinding and wheel reprofiling under coupled wheel-rail profile matching conditions. As a result, full life cycle parameter optimisation for coordinated wheel-rail maintenance has not yet been realised. Further research is therefore needed to demonstrate a closed loop framework for wheel reprofiling strategy formulation and integrated wheel-rail maintenance, as shown in Fig. 9.

4.3 Applicability across different railway systems

The applicability of the reviewed studies across different railway systems can be interpreted with caution, because high speed, heavy haul, and urban rail operations are characterised by different loading spectra, contact conditions, and maintenance constraints. In high-speed rail, operational safety and ride quality are sensitive to wheel-rail matching, equivalent conicity, out of roundness, and polygonal wear, such that even minor profile deviations can amplify dynamic excitation and noise. In this context, profile optimisation, dynamic stability control, and early detection of weak fault signatures are of particular importance. By contrast, in heavy haul systems, high axle loads and severe contact stresses make tread and flange wear, material loss, and the interaction between wear and rolling contact fatigue more dominant. Under such conditions, material selection, hardness distribution, heat treatment, surface strengthening, and cost-effective reprofiling intervals become more critical than in lighter duty applications. In urban rail and metro systems, frequent traction and braking cycles, tight curves, and limited maintenance windows place greater emphasis on flange wear, curve related damage, noise and vibration control, and rapid inspection and intervention cycles. These differences indicate that no single monitoring, prediction, or maintenance strategy can be regarded as universally optimal. Findings obtained in one railway system can therefore not be transferred directly to another without adjustment for axle load, speed range, traction and braking duty, curve distribution, track quality, and maintenance organisation. In particular, for condition-based maintenance implementation, monitoring indicators, maintenance thresholds, and intervention timing can be calibrated against system specific degradation modes and operational objectives.

5. Conclusions and future outlook

(1) During the design and manufacturing stage, the material system, tread geometry,

and manufacturing route jointly determine the baseline wear resistance and damage tolerance of the wheel, while environment adaptive design defines the lower bound of performance under extreme service conditions. During the operational service stage, wheel-rail matching and operating conditions govern damage evolution, and both geometric evolution and risk accumulation must be considered in wear and rolling contact fatigue assessment. During the diagnosis and maintenance stage, static and dynamic inspection methods are complementary, whereas reprofiling and repair or strengthening measures must be coordinated under the combined constraints of geometry, vehicle dynamics, and economic efficiency. A full life cycle closed loop framework integrating the three stages of design and manufacturing, operational service, and diagnosis and maintenance therefore represents the fundamental route to improving wheel service performance while balancing safety and cost. At present, technologies at each stage are evolving from isolated development towards coordinated optimisation. Material design is shifting from a single property focus to the multi objective coordination of strength, toughness, wear resistance, and fatigue resistance. Operation and maintenance are moving from corrective and schedule-based approaches towards predictive and condition-based maintenance. Inspection and diagnosis are advancing from static single parameter detection to dynamic intelligent diagnosis based on multisource information fusion. Nevertheless, from the perspective of engineering implementation, the chain of prediction, decision, intervention, verification, and feedback has not yet been investigated. Data silos, model mismatch, and threshold inconsistency across stages remain the principal barriers to systematic improvement in service performance.

(2) The indicator and threshold system also remains insufficiently unified. During the design and manufacturing stage, the principal indicators are material strength, hardness, and microstructural uniformity. During the operational service stage, attention shifts to equivalent conicity, wear rate, and fatigue index. During the diagnosis and maintenance stage, decision making relies more directly on indicators such as wheel diameter difference, crack depth, and vibration features. The absence of explicit mapping relationships among such stage specific indicators makes it difficult to apply a closed loop verification framework linking damage modes, observable signals, and intervention thresholds, and may consequently lead to the coexistence of over reprofiling and delayed risk response. In addition, the generalisability of predictive models and the quantification of uncertainty remain inadequate. Physics based models for wear and rolling contact fatigue are constrained by the accuracy of contact parameter identification and by computational cost, which limits their online applicability. Data driven models, by contrast, depend heavily on high quality historical data and are prone to distribution drift when transferred across lines or operating conditions. More importantly, most existing models still lack effective uncertainty quantification, leaving maintenance decisions without reliable confidence bounds. A further limitation lies in the lack of coordinated wheel-rail maintenance mechanisms. Current maintenance strategies continue to focus on either the wheel or the rail as an individual component, with insufficient consideration of profile matching, hardness matching, and damage coupling within the wheel-rail system. Rail grinding and wheel reprofiling are planned and executed independently, making it difficult to support joint decision

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making aimed at minimising life cycle cost at the system level. At the same time, a contradiction remains between the robustness and real time capability of diagnostic inspection. Dynamic inspection methods, including vibration, acoustic, and vision-based techniques, can provide high frequency online warning, but often suffer from high false alarm and missed alarm rates under complex environmental conditions such as variable illumination, rain and snow, and ambient noise. Static inspection methods, such as ultrasonic testing and profile measurement, offer higher accuracy, but are performed too infrequently to support real time decision making. An effective linkage mechanism between dynamic early warning and static verification has therefore yet to be offered.

(3) For future engineering oriented closed loop implementation, research can progress systematically along four interrelated layers, namely data integration, model fusion, coordinated decision making, and verification with feedback. First, a unified service performance indicator system and data standard can be standardised. Priority can be given to developing a standardised mapping framework linking damage mode, observable signal, assessment indicator, and intervention measure, thereby opening data interfaces across the three stages of design and manufacturing, operational service, and diagnosis and maintenance, and forming a traceable full life cycle data asset. Second, hybrid physics and data driven modelling methods can be developed. Physics based models can provide prior constraints and physical interpretability, whereas data driven models can compensate for unmodelled dynamics and condition drift. At the same time, probabilistic prediction frameworks can be introduced to quantify predictive uncertainty and provide explicit risk bounds for maintenance decision making. Third, a system level coordinated maintenance optimisation model for the wheel-rail system can be developed. Such a model can move beyond the traditional single component maintenance paradigm and support joint maintenance strategies that explicitly account for wheel-rail hardness matching, profile matching, and damage coupling, with the aim of minimising life cycle cost and achieving coordinated optimisation of reprofiling intervals, grinding intervals, and maintenance actions. Fourth, a closed loop validation mechanism covering prediction, decision, intervention, verification, and feedback can be developed. Supported by a digital twin platform, post maintenance inspection data can be fed back to optimise design parameters, calibrate predictive models, and update decision rules, thereby forming a continuously evolving closed loop optimisation capability. In parallel, for repair and improving technologies, a complete engineering validation framework can be established, covering process windows, quality control, and in service durability verification.

Table 6. Applicability of wheel degradation, monitoring, and maintenance strategies across different railway systems

Railway system	Dominant degradation features	Monitoring priority	Maintenance focus	Transferability note
High-speed	polygonal wear, out-of-roundness, stability-sensitive profile evolution	dynamic online monitoring, weak-feature detection	early reprofiling, stability-oriented thresholds	sensitive to conicity and dynamic excitation
Heavy-haul	severe wear, material loss, wear–RCF interaction	life/depth/severity tracking	cost-efficient life extension, robust reprofiling cycles	strong dependence on axle load and contact stress
Urban rail	flange wear, curve-related	frequent inspection,	rapid intervention, curve-	thresholds influenced by

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Railway system	Dominant degradation features	Monitoring priority	Maintenance focus	Transferability note
	damage, noise issues	geometry/noise indicators	wear control	braking frequency and curve radius

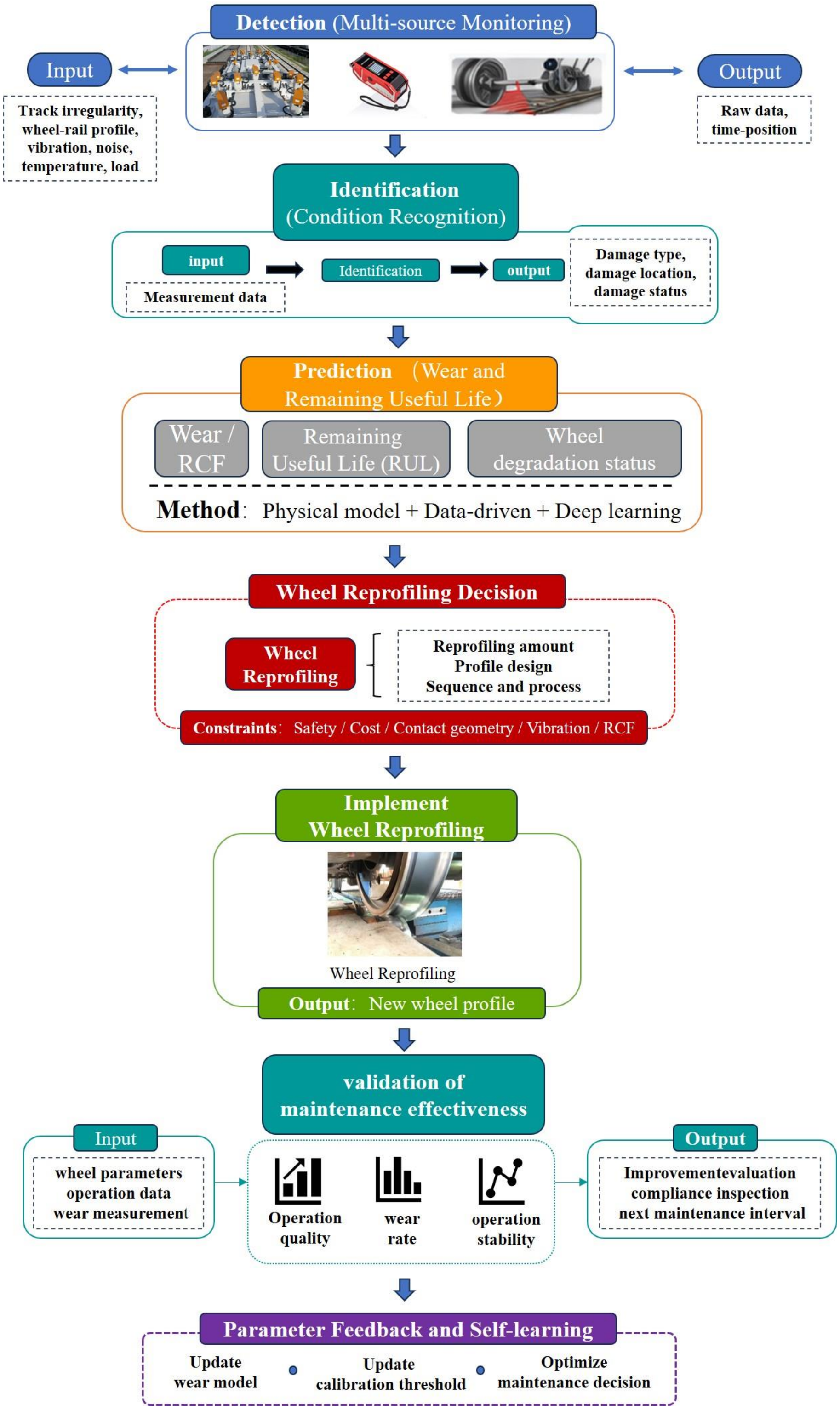

Fig 9 a closed-loop workflow for wheel reprofiling strategy formulation

Acknowledgements

This work was supported by the Major Technology Research and Development Program of the Hebei Provincial Science and Technology (24292201Z), and Hebei Province Yanzhao Golden Terrace Talent Attraction Program for Outstanding Talents (A2024004), Hebei Province's Full-time Recruitment of High-level Talent Research Project (2024HBQZYCXY014) and the Science and Technology Project of the Hebei Education Department (QN2023035, CXZX2026065).

Conflict of Interest Statement

The authors declare no conflicts of interest.

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https://doi.org/10.37965/jdmd.2026.1233