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# Fault Detection and Diagnostic Methods for Railway Systems – A Literature Survey

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## ABSTRACT

This paper presents a systematic literature survey on diagnostic methods used for railway materials and systems. The authors analyze various railway accident reports, focusing on the types of failures described and their causes. Previous review papers have addressed various aspects of railway systems diagnostics; however, most of the existing research focuses on specific parts of the rail vehicle or subsystems. In contrast, this survey focuses on railway diagnostic systems rather than general diagnostic methods used in mechanical and electrical engineering. The authors classify the types of failures and diagnostic methods that are used in rail transport into two categories: infrastructure and rolling stock. The purpose of this paper is to systematize the types of failure that occur in railway transport systems; identify the state-of-the-art means and methods of diagnostics in railway materials and systems, with particular focus on new research findings; and identify trends and possible research gaps in need of further development.

**Keywords:** railway, diagnostics, failure detection, rolling stock, railway track, railway wheel, railway bogie, railway failure.

## INTRODUCTION

Railway systems are essential components of modern transportation networks, providing efficient and reliable means of moving people and goods over long distances. However, these systems are not without their challenges, and various components within railway networks are susceptible to failure. Locomotive and railway wagon failures challenge both the safety and efficiency of railway transportation systems. Identifying and addressing the root causes of failures, implementing preventive measures, and adhering to safety standards are essential steps in ensuring the reliability and safety of railway operations. Through ongoing advancements in technology and a commitment to safety, the railway industry will continue to provide a vital and sustainable mode of transportation for the future. Track failures, signaling and communication issues, rolling stock malfunctions, infrastructure problems, and various other challenges can disrupt operations, pose safety risks, and cause substantial economic losses, and addressing these common failures requires a concerted effort from railway operators, government agencies and researchers. By investing in modernization, rigorous maintenance programs, enhanced safety protocols, and advanced diagnostic systems, failure risks can be mitigated, ensuring that railway systems continue to serve as safe and reliable modes of transportation. The most common failures of railway systems, as well as their impact on operations, safety, and the economy, are described in further detail within this paper.

This paper provides a detailed survey of the current state-of-the-art in railway track condition monitoring systems. The focus is on exploring a range of technologies and methodologies employed for track health assessment. Efficient and reliable railway systems are crucial for transporting people and goods over long distances, underscoring their importance. However, they face significant challenges due to their susceptibility to failures in various components, which impact safety, efficiency, and the economy.

Identifying and addressing the root causes of these failures, implementing preventive measures, and adhering to stringent safety standards are essential to maintaining the integrity of railway systems. The future of the railway industry lies in continued advancements in technology and a steadfast commitment to safety, ensuring a sustainable and efficient mode of transportation for years to come.

Figures 1 and 2 present an assessment of the ten-year accident report of the U.S. Department of Transportation, Federal Railroad Administration Office of Safety Analysis. The main cause of train accidents over the ten-year reporting period is described as the "Human Factor". The second most common type of train accident is "Track caused", followed by "Other types", "Miscellaneous caused" and " Motive power/equipment caused" with "Signal caused" accidents closing the ranking. The number of railroads included into the report for each year varies from 811 to 847 railroads; approximately ± 2% distribution comprises the average number of railroads taken into account. Only partial yearly data are included for 2023. The number of annual accidents remains similar, irrespective of the cause.

Derailment was the most common type of accident for every recorded year. The cause of said derailment was not specified in the report. Based on the data displayed in Figure 2, it can be assumed that most derailments are caused by human factors, followed by track-related issues and other causes.

The number of annual railway accidents that have occurred in the US in the last decade did not decrease significantly. Implementing railway operator assistance and monitoring technologies could help reduce the prevalence of human-related railway accidents. Acts of vandalisms or

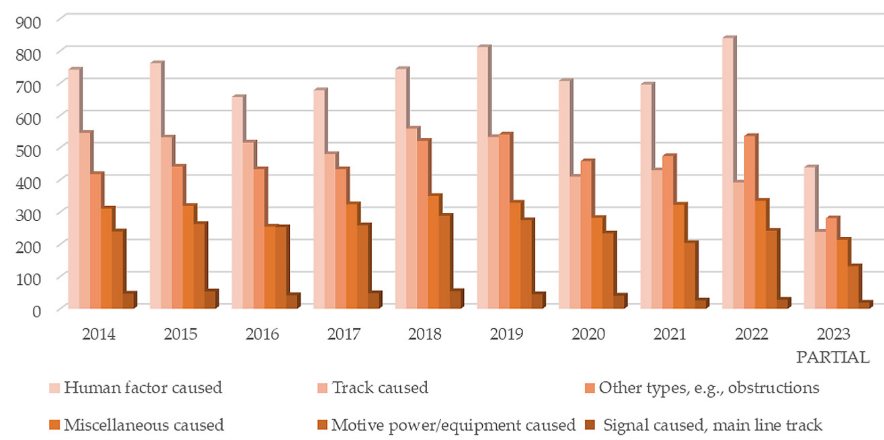


**Figure 1.** Causes of train accidents from 2014 to 2023 [1]

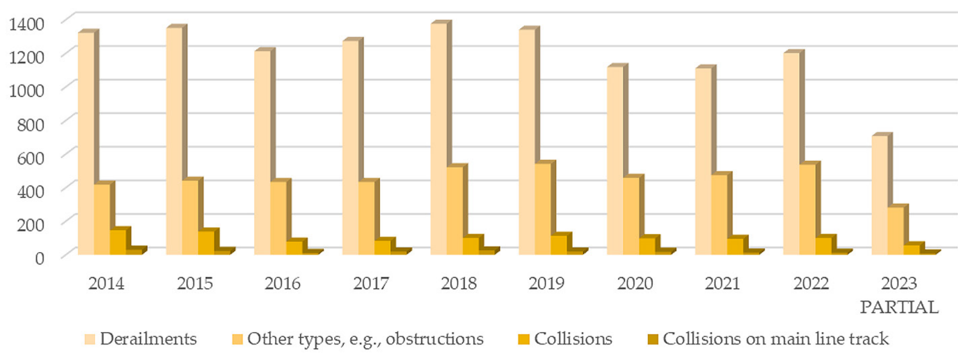


**Figure 2.** Types of railway accidents from 2014 to 2023 [1]

random events are more difficult to detect and monitor. Railway infrastructure and rolling stock conditions, on the other hand, present many possibilities for improvement which could not only reduce the number of railway accidents, but also increase passenger and freight transport reliability and make the railways more cost-effective.

Multiple review papers have discussed factors such as condition monitoring of rail vehicle dynamics [2], wireless sensor networks for rail transport [3], track condition monitoring [4, 5], [6] and crossing and switch systems [7-9]. Most of the mentioned studies focused on a specific aspect of the railway transportation system. The purpose of this literature review is to systematize the types of damage that occur in rail transport systems; identify the state-of-the-art means and methods of diagnostics in railway systems, especially new findings and research; and last, but not least, identify possible research gaps for potential development. This paper presents common railway failures, which are divided into two main groups: infrastructure and rolling stock. The same approach was adopted for diagnostic systems presented in later sections of the paper. Rewired work is presented chronologically, focusing strictly on railway diagnostic systems rather than general diagnostic methods found in mechanical and electrical engineering.

The annual number of publications registered in Web of Science and Scopus databases in last two decades was reviewed in the context of railway diagnostic systems. Two phrases – “railway fault detection” and “railway diagnostic” – were searched for in the titles, abstracts and key words of published papers. Figure 3 shows the annual number of publications containing the phrase “railway fault detection” and Figure 4 shows the annual number of papers containing the phrase “railway diagnostic” recorded in the WoS and Scopus databases from 2000 to 20 October 2023.

The number of publications relating to railway diagnostics has increased annually since 2011, indicating an increase in research interest.

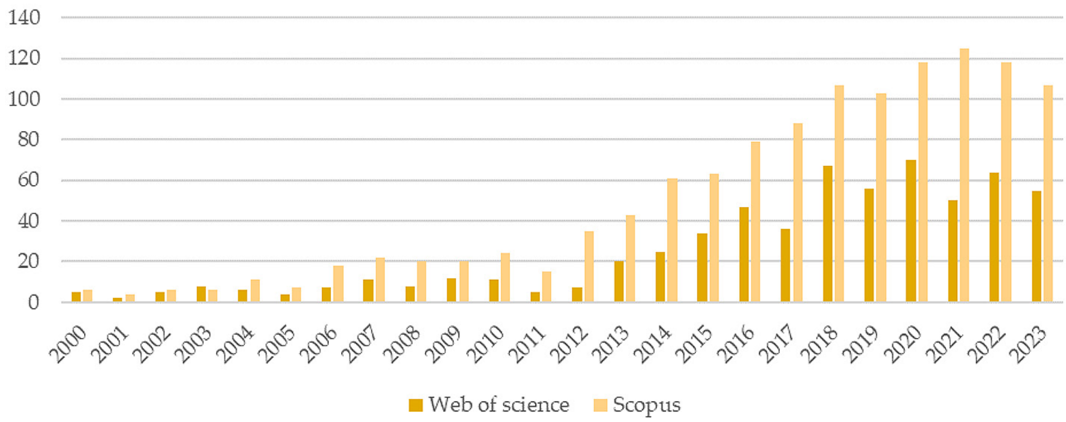


**Figure 3.** The annual number of publications containing the phrase “railway fault detection” recorded in the WoS and Scopus databases from 2000 to 20 October 2023

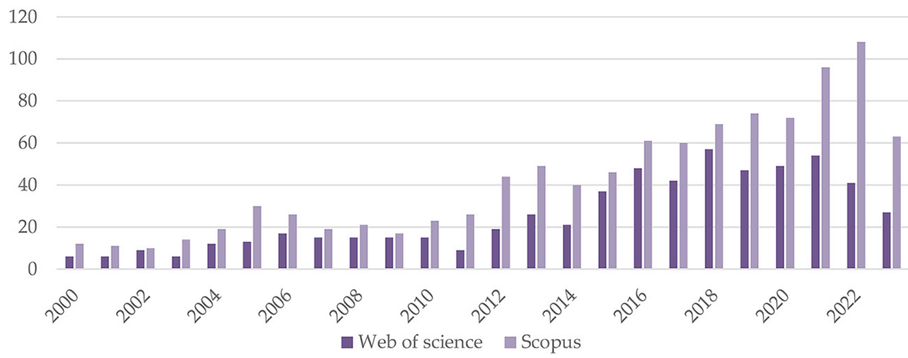


**Figure 4.** The annual number of publications containing the phrase “railway diagnostic” recorded in the WoS and Scopus databases from 2000 to 20 October 2023

However, despite increased research interest, and the various new diagnostic methods and techniques that have been proposed, the railway accident rate has not decreased significantly. Developing new measurement techniques, digital signal processing methods and big data analysis takes time, especially when it comes to realizing the real-life application of laboratory setups, as strict railway safety regulations, compatibility with other systems and data transfer capabilities must also be considered.

## FAILURES

The consequences of locomotive and wagon failure can have far-reaching impacts on railway operations, safety, and the economy. Delays and disruptions can affect schedules and logistics, with a cascading effect on the entire rail network, causing congestion and reduced efficiency. Brake failures, wheel issues, or track derailments pose significant safety hazards, leading to accidents, injuries and even loss of life. Repairing or replacing locomotives, addressing damage caused by derailments, and compensating for service disruptions lead to substantial financial burdens.

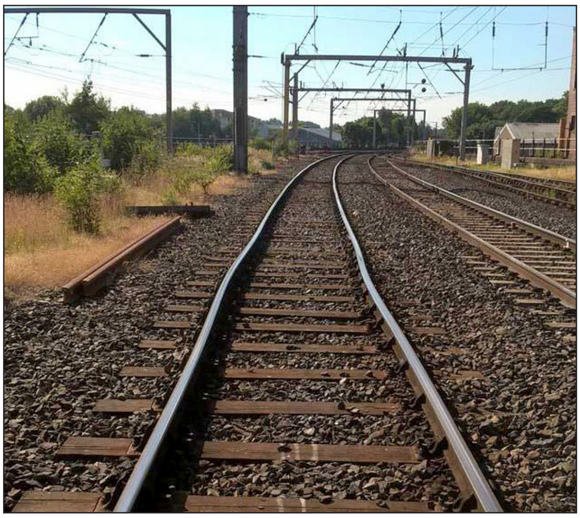

**Figure 5.** Buckled rails damaged by heatwaves [10]

**Figure 6.** A broken rail caused by a tiny defect in the foot of the rail and repeated bending under traffic [11]

## INFRASTRUCTURE FAILURES

### Tracks

One of the most prevalent areas of failure in railway systems is the track itself. The railway track, comprised of rails, sleepers (ties), ballast, and subgrade, provides the guided pathway for trains. Track failures can take various forms, including buckling (Fig. 5) due to temperature fluctuations; rail defects such as cracks (Fig. 6) and wear; ballast degradation, leading to uneven track support; and irregular track geometry. All of the above can cause derailments. These failures can disrupt railway operations, result in costly repairs and pose significant safety risks to passengers and personnel.

### Signaling and communication

Railway systems rely on signaling and communication systems to ensure safe and efficient train movements. These systems use visual or electronic signals to communicate instructions to train drivers regarding speed, route, and upcoming track conditions. Signal failures, such as broken signals or incorrect indications, can lead to accidents and delays. Communication system failures can disrupt train control and dispatch, potentially causing collisions or operational chaos.

### Infrastructure components

Infrastructure components such as switches and crossings, bridges, tunnels, and level crossings are essential elements of railway networks that must be maintained in optimal condition to ensure safe and uninterrupted train operations. Failures in these areas, whether they are the result of structural issues or wear and tear, can result in service interruptions, repair costs, and, in the worst cases, accidents that endanger passengers and crew.

### Power supply

In electrified rail systems, the power supply consists of substations, transformers, and overhead catenary systems that deliver uninterrupted electrical energy to trains. Any disruptions in this supply can halt train operations, causing significant delays and inconvenience for passengers. Therefore, ensuring a reliable power supply is crucial for maintaining the smooth functioning of railways.

### Wear and tear

Railway infrastructure consists of various components such as tracks, switches, bridges, tunnels, and level crossings. Due to heavy use, particularly in the case of heavy freight transportation, railway infrastructure is subject to continuous wear and tear. This necessitates regular maintenance and replacement of components to ensure safe and reliable operations.

### Rolling stock failures

Rolling Stock refers to the collection of locomotives, railcars, and other vehicles that move along the railway tracks. These vehicles consist of mechanical and electrical systems essential for propulsion, braking, and passenger or freight transport. The mechanical and electrical components of locomotives and railcars are prone to failure. Locomotive failures can occur for various reasons, disrupting the operation of trains and posing safety hazards.

### Drive failures

Locomotives are rail vehicles powered by engines, typically diesel or electric, that provide the necessary traction to haul trains along railway tracks. They are equipped with diverse mechanical and electrical systems for propulsion, braking, and control, crucial for ensuring safe and efficient railway operations. Diesel-powered locomotives can encounter issues such as engine overheating, fuel system problems, and injector failures, with critical reliance on fuel pumps; failures in these pumps can cause engine shutdowns. Additionally, overheating due to coolant system problems can lead to engine damage. Electric locomotives, while not immune to failure, often experience motor issues such as electrical shorts, overheating, bearing failures, or worn-out components.

### Mechanical failures

Engineering practice shows that locomotives transmission systems can exhibit various problems, including gear or clutch failures. Wheel fractures or flat spots can lead to rough rides or even derailments, while fractured or bent axles can compromise the structural integrity of the wagon and pose a serious safety hazard. Meanwhile, bogie axle bearing failures can occur due to poor lubrication, contamination, manufacturing defects or simple wear. When bearings fail, they tend to overheat, increase friction and potentially lead to derailments, posing a significant safety risk. The suspension system in bogies plays a crucial role in absorbing shocks and vibrations, providing a safe and comfortable ride. Suspension system failures can occur due to worn-out components, such as springs or dampers. Scenarios involving broken or shortened springs, as well as softening, which includes individual spring losses from a nest or crosssection degradation due to corrosion, can lead to an uncomfortable ride and increase wear on the track, requiring more frequent maintenance, while malfunctioning couplers can result in decoupling between wagons, disrupting the train's stability.

### Locomotive control systems

Issues with the locomotive's control systems, including the computerized control unit, sensors, and communication systems, can cause failures. Faulty wiring, loose connections, or electrical shorts can disrupt the locomotive's electrical systems, while problems with the air brake system, such as leaks or malfunctioning valves, can compromise the ability to stop the locomotive and wagons safely. Brake failures can lead to dangerous situations, such as loss of control or runaway trains. Brake shoes, air compressors, or brake lines can also fail. Air compressors are crucial for maintaining air pressure in the locomotives and wagons systems.

### Human factor and consequences failures

Operator errors such as improper operation or failure to follow safety procedures, as well as inadequate maintenance or repairs, can result in locomotive or wagon breakdowns. Deliberate acts of vandalism and sabotage can target railway systems, causing costly damage and disruptions. Protection of railway assets from such threats is essential for maintaining safety and operational continuity. Cybersecurity threats are another emerging concern for railway systems, as targeting control systems, signaling, or communication networks can compromise safety and service integrity.

The consequences of locomotive and wagon failures can have far-reaching impacts on railway operations, safety, and the economy. Delays and disruptions can affect schedules and logistics, with a cascading effect on the entire rail network, causing congestion and reduced efficiency. Brake failures, wheel issues and track derailments pose significant safety hazards that can lead to accidents, injuries, and even loss of life. Meanwhile, repairing or replacing locomotives, addressing damage caused by derailments, and compensating for service disruptions come with substantial financial burdens.

## RAILWAY TRACKS

In the realm of railway diagnostics, the development and application of various methods have evolved significantly over time. Initially, railways relied heavily on manual visual inspections, where personnel would physically examine tracks and rolling stock to identify any potential issues. While these inspections were crucial in ensuring safety, they were labor-intensive and often limited in scope. As technology advanced, periodic inspections became the norm, allowing for more detailed and systematic assessments. This phase saw the introduction of specialized equipment to measure track geometry and other critical parameters. The emergence of in-service vehicle monitoring systems marked a pivotal shift, utilizing existing rolling stock to continuously gather real-time data on track conditions. Further innovations brought fiber optic sensors, which provided high sensitivity and long-range monitoring capabilities. Onboard monitoring systems for rolling stock, along with vibration analysis techniques, offered non-intrusive ways to detect component health and potential failures. These advancements paved the way for integrated systems that combine multiple sensor technologies, enabling comprehensive diagnostics and predictive maintenance. The Figure 7 visually maps the progression from early methods such as visual inspections to the future direction of integrated systems utilizing multiple sensor technologies for comprehensive diagnostic capabilities.

In 2003, Bogue [12] delineated the development and utilization of a wireless-based stress monitoring system. Its scope extends to various applications, including the monitoring of railway tracks, rolling stock and substantial structures such as oil rigs and bridges.

In 2005 and 2006, Kojima et al. [13, 14] discussed the conventional methods of measuring the conditions of railway tracks using inspection vehicles. They suggested that it might be more

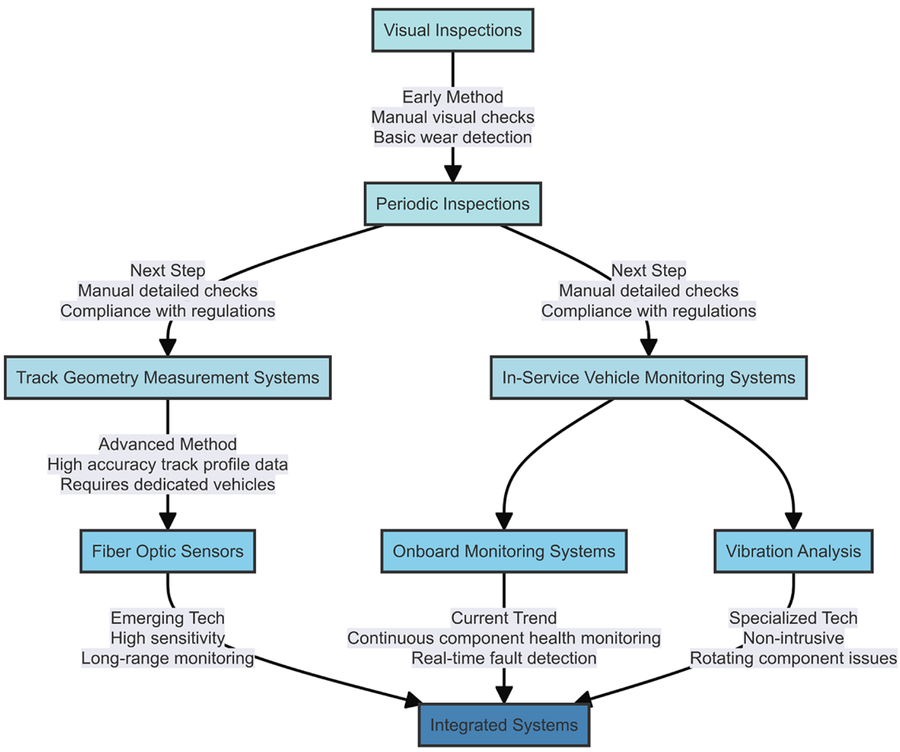


**Figure 7.** Flowchart illustrating the evolution of diagnostic methods in railway systems over time

efficient to use simple sensors, such as accelerometers, attached to commercial vehicles to evaluate track conditions. Specifically, the authors focused on rail corrugation detection through the analysis of vertical acceleration of a vehicle body over time using time–frequency analysis. The research involved conducting actual vehicle tests on a commercial rail line, which involved measuring the vertical acceleration of axle-boxes and the vehicle body. The paper demonstrated that rail corrugation could be detected based on the vertical acceleration of a vehicle body using multi-resolution analysis (MRA) with the wavelet transform technique.

In their 2006 study, Weston et al. [15] focused on the miniaturization of track recording vehicle equipment, enabling its installation on in-service vehicles for the purpose of monitoring track geometry. An alternative approach, as presented in the paper, involved attaching robust sensors, such as accelerometers and rate gyroscopes, to the bogie and axle-boxes of in-service vehicles. The sensors' data, however, had limitations, particularly in terms of gauge measurement, and the lateral movement of the wheelsets with respect to the track introduced inaccuracies. Despite these constraints, the paper emphasized that valuable information could still be derived, including estimates of mean vertical and lateral alignment standard deviations and the detection of certain track geometry faults. This information could help to inform track maintenance practices. Furthermore, the paper highlighted the potential for the motion of the bogie and wheelsets in relation to the track to provide insights into the interaction between specific vehicles and the track itself. While this information might not explicitly reconstruct track geometry, it could be used to monitor vehicle/track interaction. The paper provided illustrative examples of features observed in the bogie and axle-box data obtained from sensors installed on a Tyne and Wear Metro vehicle. These features offered insights into the vehicle's interaction with the track, although they did not directly reconstruct the track geometry.

Naderi and Mirabadi [16] discussed the application of fiber optic sensors in the railway industry. Their research evaluated the limitations and capabilities of different sensor types, including intensity-, phase-, and wavelength-modulated sensors, along with their significant parameters for railway applications. The paper also presented simulation results for Fiber Bragg Grating (FBG) and Fabry–Perot Interferometer (FPI) sensors designed for railway use, with a focus on modeling the railwheel interaction using ANSYS software. Furthermore, the authors detailed the modeling and performance evaluation of a sensor created to measure train weight under various conditions.

Hayashi et al. [17] described various methods for detecting faults in railway vehicles and tracks. They employed a model-free approach using multi-resolution analysis for fault detection in tracks from on-board measurement data. For vehicle fault detection, they utilized the interacting multiple-model (IMM) algorithm as a model-based approach. Their research included simulation studies and field tests with actual vehicles, which indicated that the proposed methods could effectively detect both track and vehicle faults.

In 2007, Weston et al. [18] focused on maintaining the alignment of railway tracks to ensure safe and efficient travel. The paper highlighted that poor track alignment could lead to issues such as ride quality problems, flange contact, and even flange climb, all of which could pose safety risks. The paper proposed that mean track alignment be estimated using sensors installed on the bogie of an in-service railway vehicle, without the need for optical or contact sensors. It outlined how either bogie lateral acceleration or yaw rate could be processed to estimate mean lateral track irregularity, with a yaw rate gyro being particularly effective, especially at lower vehicle speeds, and it did not require compensation for bogie roll effects. The paper also described an improved estimation technique achieved by inversely relating mean track alignment to bogie yaw motion. The effectiveness of this method was demonstrated using results obtained from a Class 175 vehicle. The research emphasized that continuously monitoring the lateral response of a bogie on in-service vehicles, relying solely on a yaw rate gyro, could provide valuable data regarding which areas of maintenance to prioritize, contributing to the safety and efficiency of railway operations.

Attivissimo et al. [19] developed a railway measurement system to measure wheel–rail interaction quality in real time. They specifically focused on equivalent conicity, as defined by the UIC 518 Standard. Their system used contactless optical data processing and met the accuracy requirements of the UIC 519 Standard.

In 2008, Ho [20] introduced the principles of photonic distributed sensors and emphasized the advantages of Fiber Bragg grating sensor arrays in railway applications. Their work presents initial results from field measurements conducted with local railway partners, demonstrating the effectiveness of these sensors for smart railway condition monitoring systems. Two commercial systems have been developed and are in use locally—one on rail tracks to detect wheel/rail interface responses and another onboard trains with thermal monitoring. There are ongoing efforts to promote these systems to railway operators and consultants worldwide.

Mizuno et al. [21] developed a mobile sensing unit and created a prototype for monitoring railway tracks. This unit consisted of a compact PC, a GPS receiver, an accelerometer, and an Analog/Digital Converter (ADC). It was designed to track routes and capture acceleration data from passenger vehicles, offering more frequent and higher-quality data compared to traditional railway track inspection equipment. The unit's accurate location determination, which incorporated GPS data, existing landmarks, and vehicle acceleration responses, was a significant advantage. The researchers believed that their unit held promise for efficient railway property management. The prototype's findings suggested a correlation between car acceleration responses and low-frequency track displacements, indicating that placing sensors on the vehicle floor, rather than on axles or bogies, was effective for capturing vertical track displacements.

In 2010, Mori et al. [22] designed a portable system for monitoring track conditions which was specifically tailored for easy installation on in-service vehicles. The system relied on the car body's vertical and lateral acceleration data to estimate rail irregularities. It employed a rate gyroscope to calculate the car body's roll angle, allowing for differentiation between line and level irregularities. Rail corrugation was detected by analyzing cabin noise and identifying spectral peaks. To precisely locate track faults, the system utilized GPS technology and a map-matching algorithm. Field tests, conducted with in-service vehicles, verified the system's ability to effectively estimate rail irregularity and rail corrugation conditions.

In 2011, Ward et al. [23] explored the challenges stemming from the global increase in railway passengers, which has put pressure on improving the entire system's capacity, punctuality, and cost efficiency. They underscored the role of condition monitoring in meeting these demands. The article specifically investigated the use of sensors mounted on rolling stock to monitor both infrastructure and the rolling stock itself. This approach was considered in light of contemporary rolling stock equipped with advanced communication systems and multiple sensors, offering the potential for sophisticated data analysis. The article consolidated related research that employed a common set of rolling stock sensors, covering topics such as their general application and advantages, track defect detection methods, monitoring running gear conditions and detecting absolute train speeds.

Lee et al. [24] conducted a study that compared the use of axle-box and bogie-mounted accelerometers for monitoring track conditions with in-service high-speed trains. They introduced a method that relied on Kalman filters, band-pass filters and compensation filters to estimate lateral and vertical track irregularities based on data from either axle-box or bogie-mounted accelerometers. They also used rail vehicle dynamics software to analyze the estimated results and validate their methodology.

In another study in 2012, Lee et al. [25] presented a method of estimating railway track irregularities using acceleration data from high-speed trains. Track irregularities can lead to train vibrations, making their monitoring essential for ride quality. Their method involved applying filters for stable displacement estimation and waveband classification of acceleration data. Accelerometers placed on the axle box and bogie of high-speed trains captured lateral and vertical acceleration. The study compared their approach with commercial track geometry measurement results and discussed the accelerometer placement's impact on estimated track irregularities.

Tesfa et al. [26] aimed to address the issue of bolted joint failures in industrial structures related to railway infrastructure. These bolted connections are crucial to the safe and reliable operation of tracks and trackside equipment. Current manual maintenance procedures, often involving tens of thousands of bolted joints, are costly, disruptive and susceptible to human error. The objective of Tesfa et al.'s study was to develop a sensor-equipped washer that could automatically measure the clamping force of each individual bolted joint. This technology aimed to provide a more efficient and reliable solution for maintaining the integrity and safety of these structures, reducing maintenance costs and minimizing disruptions. The paper outlines the development of the sensor technology to be incorporated into the washer, with a focus on meeting specific criteria for accurate clamping force measurement.

Ngigi et al. [27] focused on modern railway systems and their advanced monitoring techniques for maintenance. They explored condition monitoring methods that use sophisticated approaches like filtering and signal analysis for fault detection. These methods are adept at handling system complexities and variations without the need for intricate mathematical models. In practice, sensors are deployed either on the track or rolling stock, depending on the specific monitoring requirements. For instance, track-mounted sensors can monitor wheelset dynamics, while vehicle-based sensors are used to oversee the train infrastructure. The paper aimed to compile and assess contemporary techniques for monitoring railway vehicle dynamics, providing a critical evaluation of their advantages and limitations.

Chellaswamy et al. [28] aimed to enhance railway passenger comfort by reducing noise and vibration during travel. They introduced the Fuzzy Track Monitoring System (FTMS), which is to estimate track irregularities in real time. Vibration sensors on the train's axle box and bogie measured acceleration in vertical and lateral directions, allowing vibration data to be tracked and relayed to a central office. This showcased this method's potential to obtain real-time measurements and thus improve ride quality.

Bagshawe [29] explored the feasibility of using readily available MEMS (Micro-Electro-Mechanical Systems) sensors in existing train-borne track condition monitoring systems. These systems often rely on costly and relatively large inertial measurement units (IMUs). The goal was to reduce support costs and improve spare parts availability by considering MEMS sensor substitutes. The study compared a candidate MEMS accelerometer with a standard accelerometer, particularly in relation to inertial measurements in the vertical profile. The research determined the minimum performance requirements for the replacement accelerometer based on measurement system specifications. A suitable MEMS device was integrated into the system. Trial data collected at various speeds were analyzed, and the results indicated that the MEMS accelerometer was theoretically suitable for use at speeds as low as 25 mph. Despite some practical limitations related to its installation, the trial showed that the MEMS accelerometer closely matched the performance of the standard accelerometer, especially at speeds greater than 50 mph. Further trials with improved installation positions were suggested for future investigation.

In 2013, Chellaswamy et al. [30] aimed to address the primary issue affecting passenger comfort in railway transportation: vibrations, predominantly stemming from track variations. Their work focused on reducing these vibrations by eliminating track irregularities through an innovative system known as the Intelligent Track Monitoring System (ITMS), which is designed to identify and rectify track aberrations. The system uses MEMS technology, which is known for its reliability, employing sensors placed on both the axle box and bogie in both vertical and lateral directions. A controller continuously monitors GSM signals and processes data accordingly, with GPS used to determine location when the GSM signal strength is low. ITMS autonomously detects irregularities and communicates their locations to a central office. The system utilizes Continuous Wavelet Transform (CWT) to estimate output, and the study's results confirmed that the proposed monitoring system significantly improves passenger ride quality.

Qin et al. [31] created an onboard device for diagnosing track faults in railway condition monitoring. The device, which is designed to be installed on in-service vehicles, identifies track faults by analyzing the unique vertical and lateral acceleration patterns of the axle-box, bogie, and car-body. To assess the track's condition, the vibration signal is initially transformed from the time domain to the frequency domain. Principal component analysis (PCA) and support vector machines (SVM) are then used to calculate probabilities of track faults. The Dempster–Shafer (D-S) evidence theory is employed to combine information from various sources for track fault diagnosis. When a fault is detected, the system immediately sends an alert to the monitoring center, ensuring the safety of subsequent vehicles. Experiments using three accelerometer signals from different positions validated the algorithm's effectiveness in estimating rail irregularities and diagnosing track faults.

In 2014, Tsunashima et al. [5] developed a track condition monitoring system for conventional railways. In their work, they estimate track irregularities by analyzing vertical and lateral acceleration, as well as the roll rate of the train car. They also detect rail corrugation by analyzing cabin noise through spectral peak calculation. To pinpoint the location of track faults, they use a combination of GPS and a map-matching algorithm. The authors have also introduced a new and improved device designed for practical use, offering higher performance. Data collected by the system can be stored in an onboard memory or transmitted to a data server via a cellular connection. This compact on-board device ensures regular monitoring of railway tracks to maintain and secure the safety of the railway system.

In another study, Tsunashima et al. [32] focused on enhancing railway safety and comfort through track maintenance based on track geometry data. They developed a track condition monitoring system that was primarily used to identify areas requiring track tamping for smoother rides. Their innovation involved using simple car-body acceleration measurement devices, which simplify maintenance procedures. While car-body acceleration data differ significantly from track geometry data, the paper demonstrates the feasibility of estimating Shinkansen track geometry solely from car-body motion. They employed a Kalman filter (KF) in an inverse problem to estimate track irregularities from car-body motions, achieving accurate vertical track irregularity estimation for practical use.

Reiterer et al. [33] focused on the importance of regular condition monitoring for railway maintenance and safety. They recommended using running inspection trains or stationary checkpoints equipped with advanced measurement systems. These systems must operate swiftly and accurately under challenging conditions. Laser scanning was identified as an efficient method for precise measurement of railway infrastructure, offering high point densities and millimeter level accuracy. The paper provides an overview of laser scanning methods, their advantages and their disadvantages, and describes specific railway measurement systems developed by the authors.

Yeo et al. [34] utilized an inertial measurement unit (IMU) with three high-quality accelerometers and three gyroscopes attached to the bogie of a working railway vehicle. They processed the IMU data along with a tachometer signal and GPS information to monitor the location, orientation and trajectory of the bogie, which allowed them to assess the condition of the track geometry. They continuously monitored these data as the vehicle traveled along its normal routes, enabling the detection of changes in track geometry with fine temporal granularity. The research described the applications of such precise track geometry data and the development of automated processing methods to extract the desired information. The primary goal was to observe track geometry through various stages, including renewals, degradation, and maintenance, to understand the development of faults and the effectiveness of maintenance efforts.

In their field trial, Roveri et al. [35] utilized a Fiber Bragg Grating (FBG) sensor array system to conduct real-time monitoring of railway traffic and assess the structural health of both the railway track and train wheels. They executed these tests on Milan's second line of the metropolitan underground, deploying over 50 FBG sensors along a 1.5 km rail track. These tests were conducted during daily passenger rail transport, with trains reaching speeds of approximately 90 km/h. Measurements were continuously taken over a six-month period at a sampling rate of approximately 400 Hz. The abundance of data and sensors enabled precise statistical analysis of measurement data. Dedicated algorithms allowed for the estimation of rail and wheel wear, as well as key traffic parameters such as axle count, train speed, load, and the potential identification of localized imperfections in the near future.

Hodge et al. [36] explored the recent advancements in sensing technologies and the decreasing cost of sensor devices, which have driven the widespread adoption of condition monitoring in various domains, including systems, structures, vehicles and machinery. They highlighted the significance of wireless communication and mobile ad hoc networking technologies, along with the ability to integrate devices, leading to the use of wireless sensor networks (WSNs) for monitoring railway infrastructure and vehicle health. Condition monitoring through WSNs reduces the need for human inspections, enables earlier fault detection, preventing escalation, and enhances safety and reliability in the railway industry. The paper provided a comprehensive survey of WSN technology for railway monitoring, focusing on practical engineering solutions, the types of sensor devices employed, their specific applications, and the configurations and network topologies used. It also compared and contrasted the motivations and advantages and disadvantages of these sensor setups in the context of railway monitoring.

In 2015, Weston et al. [37] discussed the current status of monitoring track geometry condition via in-service vehicles. They described the technology used, the challenges associated with processing, location determination and how this field has evolved over the past decade. The paper emphasized the need for ongoing research. While in-service vehicle-based track geometry monitoring has already become a reality, there is room for improvement regarding this technique.

The paper highlighted the value of repeated track observations for detecting geometry degradation, informing maintenance decisions and evaluating maintenance effectiveness. It mentioned unattended track geometry measurement systems used worldwide, with underutilized data primarily generating reports. The paper also described different monitoring approaches, including simpler systems, experimental methods and systems indirectly assessing poor track geometry.

In 2015 and 2016, Tsunashima et al. [38], [39] developed a track condition monitoring system for enhancing railway safety. They achieved this by equipping in-service vehicles with sensors and GPS systems to capture real-time vehicle vibrations. Their innovation lies in the use of a compact on-board sensing device and specialized diagnosis software. The software detects track faults by analyzing the root mean square (RMS) of the car-body's acceleration and conducts time–frequency domain analysis using wavelet transforms. The researchers also applied a Kalman filter to solve an inverse problem, estimating track irregularities based on car-body acceleration data. This estimation method was employed to assess track irregularities in terms of track geometry and 10 m-chord versine in the longitudinal direction. The results demonstrated that this estimation technique effectively supports track condition monitoring with acceptable accuracy for conventional railways. Field tests conducted on local railway lines confirmed the system's practical effectiveness.

In 2016, Ilie and Stancalie [40] addressed the safety concerns associated with railway defects, particularly broken rails, which jeopardize railway operations. Their goal was to establish a reliable and accurate railway monitoring system with potential for remote use. They conducted a series of extensive experiments to explore the feasibility of using optical fiber sensors for railway monitoring, with particular focus on how optical fiber sensors respond to temperature and strain variations to assess railway expansion, aiming to create a proof of concept for a dependable monitoring system.

Maddison and Smith [41] developed wireless sensor networks for remote geotechnical monitoring, incorporating low-cost, self-contained, and self-configuring wireless sensors. These sensors are easily installed without the need for extensive wiring. They have made significant advancements in areas such as extending sensor node battery life, improving network robustness, data throughput, and sensor precision. This technology has performed successful monitoring in various challenging environments, such as rail tunnels and trackbeds, fulfilling the needs of asset holders such as London Underground and Network Rail. The system demonstrated precise measurements of tunnel deformation during engineering projects, and it can also effectively monitor railway tracks, measuring changes in track cant, twist and longitudinal rate of change with high precision and stability. The wireless solution was preferred over optical options due to its stability, repeatability and resistance to environmental challenges. A growing trend toward wireless monitoring of rail assets is anticipated due to the advantages it offers.

Lienhart et al. [42] have introduced innovative methods for the continuous monitoring of railway tracks and vehicles across extensive distances in the European railway network, utilizing distributed fiber optic sensing (DFOS) techniques. They began by affixing fiber optic strain sensing cables to railway tracks to detect strain changes caused by rail deformations. This was monitored through distributed Brillouin measurements (BOTDA, BOFDA). This system enables the early identification of potential damage from natural events, such as mudflows, avalanches, floods and landslides, allowing for swift implementation of countermeasures. In a second approach, optical communication cables already in place alongside modern rail infrastructure were used to detect flat spots on railway wheels. These flat spots, if left unaddressed, can damage tracks and may lead to derailment. The researchers used distributed acoustic sensing (DAS) for continuous monitoring of trains and extraction of individual profiles indicating flat spots. Importantly, this system requires no additional infrastructure, apart from the optical time-domain reflectometry (OTDR) instrument. Through field installations in the Austrian railway network, the effectiveness of both BOFDA and OTDR systems is demonstrated, allowing for the ongoing monitoring of incidents and deformations. This approach ensures the continuous assessment of railway tracks and vehicles over long distances.

Xu et al. [43] developed a method for identifying track irregularity faults that can cause abnormal train vibrations, leading to poor ride quality and derailment. Their approach, based on Evidence Reasoning (ER) rules, uses data from accelerometers mounted on the axle-box and car-body of in-service trains. Their method uses statistical analysis of sample data to generate diagnostic evidence, combines this evidence using ER rules and subsequently estimates irregularity displacement. It then identifies the dynamic levels of track irregularity based on the estimated displacement and relevant management standards. An experiment conducted on a Chinese railway line demonstrated the superior accuracy of this method compared to classical neural net-work-based approaches.

Balouchi et al. [44] collaborated with the Rail Safety and Standards Board and the Institute of Railway Research to develop the Siemens Tracksure track monitoring system. This system leverages the existing GSM-R cab radio in all UK trains, equipped with a sensor card to detect track condition via three-axis train vibrations. Tracksure's onboard signal processing reduces data transfer requirements. For voided switches and crossings (S&C), the system uses GPS location to pinpoint asset numbers, increasing accuracy and streamlining maintenance efforts. The Ground System combines data from multiple trains to achieve more precise void detection and fewer false alarms. It also offers automated void reporting, facilitating efficient maintenance planning. Nexus Tracksure can be easily activated on all UK trains, forming a comprehensive network-wide track monitoring system. Recent trials demonstrated its effectiveness in detecting voided sleepers under various track types, with excellent repeatability. Upcoming Network Rail upgrades will enhance the system with GPS connectivity, improving preventative maintenance and safety.

In 2017, Chellaswamy et al. [45] proposed a new method for monitoring rail track irregularities, enhancing transportation safety. Traditional track inspections are infrequent and often occur at night when service is minimal, meaning that critical issues may be overlooked. Thus, the focus has shifted to in-service vehicle monitoring. These researchers' approach involves using acceleration data from both the bogie and car body to detect track irregularities. These data inform track alignment analysis through mathematical modelling and frequency response evaluation. Both simulations and real-world tests confirmed the system's effectiveness. They differential evolution (DE) algorithm was used to optimize irregularity values from accelerometers in the axle box and bogie. Simulation results at various train speeds demonstrate the efficacy of their approach compared to traditional track geometry measurements.

Seraj et al. [46] have developed RoVi, a smartphone-based framework for the continuous monitoring of ground transport infrastructures. RoVi tracks various indicators such as railroad track geometry features and road/bike path roughness, providing real-time, fine-grained data through smartphones' inertial sensors. It fills the gaps in monitoring caused by infrequent inspections using a crowd-sensing approach. RoVi is a valuable tool for engineers and maintenance planners, offering features and indicators for asset management and maintenance planning. It extracts this information from smartphone data, using adaptive signal processing and geolocation visualization. The system's performance has been rigorously evaluated and has proven effective in continuous infrastructure monitoring.

Muthukumar and Nallathambi [4] have investigated the growing use of sensing technologies in recent years, as these technologies have become more cost-effective. This expansion has led to increased condition monitoring of various systems, structures, vehicles, and equipment. They highlight the role of advancements in networking technologies, such as wireless communication and mobile ad hoc networking, in conjunction with the integration of sensor devices. Wireless sensor networks (WSNs) have found applications in the railway industry for monitoring infrastructure like bridges, rail tracks, track beds, and track equipment, as well as vehicle safety monitoring. This technology reduces the need for manual inspections, identifies issues before they escalate, and enhances safety and reliability, which are critical to the development and expansion of railway systems. Their project explores the use of WSN technology in the railway sector, focusing on systems, structures, vehicles, and machinery. It also examines practical engineering solutions, including the types of sensor devices used, their applications, and various sensor configurations and network topologies. The study aims to provide a comparative review of their advantages and disadvantages.

Groos et al. [47] have addressed the significant maintenance costs associated with railway tracks, which often involve reactive measures. In their paper, they propose a solution utilizing embedded sensors on in-service vehicles for daily track condition monitoring. This shift from reactive to proactive maintenance aims to reduce costs significantly. Their work outlines a framework and the initial results of a prototype system for quasi-continuous monitoring of short-wavelength defects in railway tracks, like rail corrugation. The prototype was tested on a shunter locomotive in Germany, collecting data over a four-month period for algorithm development and evaluation. Data from acceleration sensors, combined with infrastructure information, pass through a data management system. This process involves georeferencing, feature extraction, and intelligent data analysis, with results visualized for infrastructure operators through a web interface.

Chudzikiewicz et al. [48] focused on demonstrating the feasibility of estimating track condition using acceleration signals derived from axle-boxes and car-body motions. They present the results of a preliminary investigation on a test track and supervised runs on Polish Railway Lines, involving an Electric Multiple Unit (EMU-ED74) with a prototype track quality monitoring system installed onboard. Their prototype uses a track quality indicator (TQI) algorithm based on a modified Karhunen–Loève transformation to process acceleration signals and extract principal dynamics from the measurement data. They compare these results with other methods used to evaluate track quality, including the synthetic coefficient Jsynth and five defectiveness parameters (W5). Their findings indicate that estimating track condition with acceptable accuracy is achievable for in-service applications, facilitating the development of cost-effective maintenance strategies.

Zhang et al. [49] have implemented Fiber Bragg Grating (FBG) sensing technology for real-time monitoring and early warning of high-speed railway track conditions in China. They established a sensor network with FBG sensors on the tracks to continuously monitor variables such as track temperature, displacement, and strain. The collected data are processed and analyzed using FBG demodulators. They also developed a temperature prediction model based on the relevance vector regression algorithm, enhancing the prediction accuracy. This system is currently in use on the Guangzhou–Shenzhen–Hong Kong high-speed railway, successfully providing early warnings regarding track conditions.

In 2018, Ngamkhanong and Kaewunruen [50] focused on the role of railway systems in modern transportation, highlighting the increased demand for both passenger and cargo transport. They emphasized the need for condition monitoring to assess railway track health, particularly in the face of harsh conditions and heavy loads. Their work reviews the various sensors used for monitoring railway track infrastructure, offering insights into their applications during extreme events. The aim of their research was to improve track inspection, damage detection, and predictive maintenance strategies, ultimately supporting cost-effective management within the railway industry.

Känsälä et al. [51] explored the application of cost-effective real-time sensors and the Industrial Internet of Things (IIoT) for proactive asset management in the rail traffic industry. Recognizing that railways are long-lasting infrastructure assets, even small improvements in efficiency and cost can have a substantial impact on overall life-cycle costs. Their study demonstrates the use of wireless three-dimensional acceleration sensors to monitor track conditions. Data collection was conducted in October 2016 on a Finnish Railways-operated railway line. A sensor was attached to a train unit, and train acceleration on a track segment was repeatedly measured at varying speeds. To enhance the collected data, map-matching and Bayesian filtering techniques were applied to improve the accuracy of Global Positioning System (GPS) location data. The filtered acceleration signals were analyzed, and any anomalies detected were compared to known parameters such as bridges and switches. The results of their testing confirm the feasibility of this concept. They also discuss the potential implications of this approach for proactive asset management of track networks and the application of statistical process control-based monitoring for track condition.

Milne et al. [52] addressed the use of low-frequency vibrations for assessing railway track condition and performance. Typically, the displacements that describe track movement under train loads are derived from velocity or acceleration signals. However, signal processing artifacts and wheel-to-wheel variability make interpreting these measurements challenging. Consequently, track deflections are often inspected rather than analyzed through systematic methods, limiting the practical utilization of track vibration data for condition or performance monitoring. Their study introduces a novel approach that leverages the cumulative distribution function of track deflection to identify the at-rest position and interpret typical track movement based on displacement data. This technique can correct at-rest position shifts in velocity or acceleration data, determine the ratio of upward and downward movement, and align data from multiple sensors to a common reference point to visualize deflection relative to distance along the track. By automating the characterization of track displacement, this method enables the utilization of large volumes of track vibration data for condition monitoring.

Tešić et al. [53] introduced the Vehicle/Track Interaction Monitor (V/TI Monitor), a modern system that employs accelerometers to assess the railway infrastructure's quality. This technology captures and characterizes the dynamic behavior of vehicles interacting with the track. The VTI-TQI software was created to identify and analyze numerous common scenarios in rail transportation in which various irregularities coincide. This system can also predict the future progression and expansion of these irregularities by generating appropriate deterioration trends.

Roth et al. [54] illustrated how positioning concepts can facilitate the real-time condition monitoring of railway tracks. In their study, they emphasize that precise georeferencing of monitoring data is achievable through the fusion of GNSS and IMU measurements with a railway network map. Their approach addresses this offline positioning challenge in two stages. They begin by estimating path hypotheses based on GNSS data and the railway map. Next, they employ a nonlinear Rauch–Tung–Striebel smoother to provide on-track positions and speeds in path coordinates. These methods are integral to a track condition monitoring system developed at DLR and have been validated using actual data from the harbor railway network in Braunschweig, Germany.

Tam et al. [55] introduced a railway health condition monitoring system founded on an optical fiber sensing network. This system has the potential to enable predictive maintenance in the railway industry. The researchers harnessed machine learning to create models capable of detecting and classifying various track defects, including rail corrugations, dipped weld joints, and rail crossings.

In 2019, Chia et al. [6] conducted a comprehensive review of the application of inertial sensors, including accelerometers and gyroscopes, for monitoring transportation asset conditions. The study explored aspects such as sensor specifications, sensor placement, and signal processing techniques to provide valuable insights into this field, with particular focus on evaluating the associated challenges and opportunities for improving railroad track condition monitoring. Lu et al. [56] developed a wireless rechargeable sensor node system for monitoring urban rail corrugation. Their system includes an energy generator that uses electromagnetic induction, a DC-DC booster converter, wireless sensor nodes and an analysis interface using Littlewood–Paley wavelet transform methods. They established a vehicle–track interaction model to predict railway track responses with rail corrugation. Field testing was conducted to validate their theoretical predictions, and the power consumption of sensor nodes was assessed. Their case study demonstrated the identification of rail corrugation defects by analyzing rail acceleration signals using Little-wood–Paley wavelet analysis.

Chandran et al. [57] developed a train-based differential eddy current (EC) sensor system to detect rail fasteners. This system uses electromagnetic induction, with an alternating current-carrying coil to create an EC on the rail and nearby conductive materials, and a pick-up coil to measure the resulting field. Their paper describes the theoretical background and application of this EC sensor system for rail fastener condition monitoring, with experimental results from both laboratory and field measurements. Field tests were conducted along a heavy-haul railway line in Sweden, and the results showed that the method could detect individual fastening systems from a height of 65 mm above the rail. The system also identified missing clamps within fastening systems by analyzing a time-domain feature of the measurement signal.

Hamadache et al. [7] conducted a comprehensive review of fault detection and diagnosis (FDD) techniques for railway switch and crossing (S&C) systems. These complex systems involve various components and technologies, making them susceptible to failures and malfunctions that may disrupt railway operations and safety. Their paper serves as an overview of the current state of FDD methods for railway S&C systems, providing valuable insights for researchers, railway operators, and experts. It aims to facilitate the development and adoption of effective FDD techniques, contributing to the advancement of condition-based maintenance and the safe operation of high-speed trains in the railway industry.

Farkas et al. [58] conducted a study driven by the increasing frequency of passenger and freight trains globally, which emphasizes the need for more extensive track monitoring and rail inspection. They focused on the wheel–rail contact forces, which result from both static axle loads and dynamic effects stemming from track superstructure vibrations, as significant contributors to railway track degradation. Their research delved into measurements of track irregularities, which are traditionally used to assess the current condition and quality of railway lines, with a particular focus on compact inertial measurement systems (IMUs). This paper explored the components, installation, and fundamental measures of track quality using motion sensors such as accelerometers and gyroscopes, which were strategically placed on the vehicle. It also briefly touched upon the basics of inertial navigation and the kinematics of translational and rotational train motions for obtaining orientation, velocity and position data.

In 2020, Bhardwaj et al. [59] developed a continuous condition monitoring system to detect and locate irregularities in railroad tracks using inertial sensors on revenue service trains. They addressed the challenges of inaccurate geospatial position estimates from GPS receivers and non-uniform sensor sampling, which introduced noise and reduced signal strength. To improve the signal-to-noise ratio, they introduced a method suitable for various signal filtering approaches. By analyzing the frequency window of the energy and variance of ensemble averaged Fast Fourier Transforms (FFTs), the method determined the best cut-off frequency for filtering. Their results showed that applying a low-pass finite impulse response filter with the selected cutoff frequency improved the signal-to-noise ratio, demonstrating the method's effectiveness and practicality.

Aung et al. [60] aimed to address the traffic congestion issues in Yangon, which have intensified due to a rapid increase in the city's population and car numbers. They focused on the importance of maintaining railway tracks for efficient rail transportation as a solution. To monitor rail track conditions for early damage detection, they employed onboard sensor measurements using a smartphone's accelerometer, which could sense irregularities during train travel. They also harnessed satellite image analysis, particularly phased-array-type L-band synthetic aperture radar images, to detect rail track irregularities using the interferometric technique. This approach allowed for effective estimation of rail track conditions.

Liu and Markine [61] investigated the reasons behind the rapid deterioration of a railway crossing. They utilized sensor-based instrumentation to assess the crossing's dynamic performance and validated their findings using a multi-body system (MBS) model that simulates the interaction between vehicles and the crossing. Through field inspections, measurements, and simulations, they identified that the rapid degradation of the crossing was primarily attributed to high wheel–rail impact forces caused by the hunting motion of passing trains. Furthermore, they revealed that track geometry misalignment ahead of the crossing triggered this hunting motion. These findings emphasized that crossing degradation might not solely originate from issues within the crossing itself but could also stem from problems in nearby track structures. The study's outcomes were integrated into a railway crossing condition monitoring system, allowing for timely and targeted maintenance actions.

Wilk et al. [62] addressed the challenge of digital filtering in the context of mobile global navigation satellite system (GNSS) measurements to accurately determine railway track coordinates. They introduced a measurement technique employing a platform equipped with multiple strategically placed GNSS receivers, two of which determined the directional base vector of the platform. These receivers operated in real-time kinematic (RTK) mode with a high measurement frequency and allowed result correction in post-processing. The article also delved into the assessment of measurement quality from GNSS receivers and their preparation for further processing, which involved geometrically constrained parameters of the base vector and specialized digital filtering. Their results confirmed the effectiveness of this GNSS signal processing approach.

In 2021, Shah et al. [63] conducted a study focused on enhancing fault diagnosis in railway condition monitoring. They aimed to improve the traditional methods used in underdeveloped countries, which rely on manual extraction of track data using push trolley/train-based track recording vehicles (TRV). This manual process is labor-intensive and subjective, impacting the accuracy of fault diagnosis. To address this issue, the researchers introduced a prototype called "Muhafiz," an automated and portable TRV with a novel design based on axle-based acceleration methodology. Through site-specific experimentation, they demonstrated that Muhafiz is 87% more efficient than the traditional push trolley-based TRV system, significantly improving railway condition monitoring and safety.

Kukulski et al. [64] aimed to diagnose the condition of continuous welded tracks, with particular focus on measuring rail displacements during operation. Their work addressed the influence of thermal stresses on rails, which are affected by temperature changes and climatic conditions. They introduced an original and effective analytical method based on experimental research to diagnose the track's condition and provide recommendations for repair or maintenance. Two scenarios were considered: tracks under load and tracks without load. The authors derived empirical formulas for calculating rail temperature and longitudinal force based on ambient temperature, particularly for straight tracks with 60E1 rails, no engineering structures, conventional surfaces, wooden sleepers, and high train traffic. The results demonstrated very high accuracy, with a correlation coefficient (R2) of ≥ 0.995, which validated the precision of their proposed method.

Zvolenský et al. [65] conducted research with a focus on railway vehicle maintenance for safety, passenger comfort and cost-efficiency. Their study explored the application of acoustics to diagnose the technical condition of railway vehicles while they are in operation. They monitored the condition of individual carriages and compared their noise levels. The paper also discussed potential practical applications for effectively reducing noise in railway carriage operations.

Balcı et al. [66] explored the integration of advanced technologies such as artificial intelligence (AI), the internet of things (IoT) and big data in the context of railway systems. They emphasized the importance of effectively detecting track faults and conducting maintenance to ensure the safety of railway operations. The researchers highlighted the current use of image processing and machine learning for automated track inspections but identified shortcomings regarding the integration of these technologies into railway tracks. Their work compared traditional and smart approaches to track inspection and maintenance, pinpointing areas in need of improvement. The researchers also discussed the potential impacts of using smart systems on the overall life cycle of railway structures.

In 2022, Daniyan et al. [67] developed an inspection and diagnostic robot for enhancing rail infrastructure integrity. This robot was designed to detect various issues such as cracks, corrosion, missing clips and wear on rail tracks. It incorporates infrared and ultrasonic sensors for obstacle avoidance and crack detection, 3D profilometers for wear detection, high-resolution cameras for real-time imaging and colour sensors for corrosion detection. The robot's image processing capabilities allow in-depth analysis of detected cracks and corrosion. The study involved computer-aided design and modeling of the robot, and simulation in MATLAB 2020b. The results presented frameworks for wear, corrosion, missing clips, and crack detection, along with design data for the integrated robotic system. The simulation results demonstrated the system's significant sensitivity and accuracy in fault detection. The work introduces a novel autonomous system for proactive rail track monitoring and defect detection, with the potential to increase rail network capacity and availability.

Bolshakova et al. [68] conducted an analysis of small-sized inertial measuring systems that utilize sensors placed near the wheel/rail contact area. This design enables the simultaneous monitoring of mechanical and acoustic effects generated by the passage of faulty track elements using a single device. The study examined the mechanical and acoustic characteristics of the car/rail track system and explored methods for kinematic analysis and vibroacoustics, which can be applied to assess the condition of structural components in both the railcar and rail track.

In 2023, Tsunashima et al. [69] developed a system for monitoring railway track conditions, which is crucial for ensuring safety. Traditional track maintenance on regional railways faces financial challenges and a lack of manpower. To address this, the researchers created a diagnostic system involving onboard sensors on in-service vehicles that measure car body vibration acceleration to assess the condition of the track. Long-term measurements were conducted, and changes in track conditions were evaluated using the vibration data. The study successfully identified degraded track sections and demonstrated the system's effectiveness in confirming track maintenance results. They also proposed a method for improving train position determination using yaw angular velocity and introduced a technique for more precisely assessing track condition through time–frequency analysis of car-body vertical acceleration. Zanelli et al. [70] addressed the critical need for railway infrastructure monitoring to ensure transportation reliability and safety. While diagnostic trains are typically used for this purpose, they are infrequent on main lines. The researchers developed a wireless system capable of monitoring vehicle dynamics and detecting potential track issues in real time. They achieved this by analyzing acceleration RMS values within specific frequency ranges, using data collected during extended experimental campaigns. This method enables continuous monitoring and offers an affordable and easily installed solution for freight wagons. Ultimately, the system can enhance maintenance strategies for conventional lines, along which diagnostic train runs occur at long intervals. In 2024 Pal and Datta [71] study tackles the challenge of timely fault detection in railway tracks, crucial for safety and efficiency. Traditional methods are complex, and recent AI approaches lack a systematic weighting system for optimal performance.

This research bridges the gap by assigning weights to key AE signal parameters (amplitude, frequency, etc.) based on their importance. This guides an artificial neural network (ANN) model to focus on critical data points for improved fault detection accuracy. Extensive testing

**Table 1.** Types of measurements/method used for track diagnostics

| Main classification | Type of measurement/method | | References |
|---|---|---|---|
| Onboard | Accelerometer | | Kojima et al. [13], [14]<br>Mizuno et al. [21]<br>Lee et al. [24]<br>Lee et al. [25]<br>Chellaswamy et al. [28]<br>Bagshawe [29]<br>Chellaswamy et al. [30]<br>Qin et al. [31]<br>Tsunashima et al. [32]<br>Tsunashima et al. [38], [39]<br>Xu et al. [43]<br>Balouchi et al. [44]<br>Chellaswamy et al. [45]<br>Groos et al. [47]<br>Chudzikiewicz et al. [48]<br>Känsälä et al. [51]<br>Teši et al. [53]<br>Roth et al. [54]<br>Shah et al. [63]<br>Zanelli et al. [70] |
| | | + gyroscope | Weston et al. [15], [18]<br>Ward et al. [23]<br>Yeo et al. [34]<br>Seraj et al. [46]<br>Chia et al. [6]<br>Farkas et al. [58]<br>Bhardwaj et al. [59]<br>Aung et al. [60]<br>Bolshakova et al. [68]<br>Tsunashima et al. [69] |
| | | + microphone | Hayashi et al. [17]<br>Mori et al. [22] |
| | Optical/visual | | Attivissimo et al. [19]<br>Reiterer et al. [33] |
| | Others | | Chandran et al. [57]<br>Wilk et al. [62] |
| Track side | Strain gauge | | Bogue [12] |
| | Fiber optic | | Naderi and Mirabadi [16]<br>Ho [20]<br>Roveri et al. [35]<br>Ilie and Stancalie [40]<br>Lienhart et al. [42]<br>Zhang et al. [49]<br>Tam et al. [55] |
| | Force | | Tesfa et al. [26]<br>Kukulski et al. [64] |
| | Vibration | | Milne et al. [52]<br>Lu et al. [56]<br>Liu and Markine [61] |
| | Others | | Maddison and Smith [41]<br>Muthukumar and Nallathambi [4] |
| Others works | | | Nigi et al. [27]<br>Hodge et al. [36]<br>Ngamkhanong and Kaewunruen [50]<br>Hamadache et al. [7]<br>Balcı et al. [66]<br>Daniyan et al. [67] |

demonstrates the effectiveness of this approach in both lab simulations and real-world scenarios. Table 1 categorizes track diagnostic methods into onboard (mounted on trains) and trackside (fixed to the track) systems. It details specific techniques like accelerometers, fiber optics, and vibration analysis, along with references for further exploration.

Rolling stock diagnostic systems can be divided into three main categories: wheels, bogies, and other. Wheel surface damage and wear detection systems are among the most well-researched topics. Recently, there has been increasing focus on suspensions systems, as well as diagnostics of freight wagons and other locomotive or wagon sub systems.

Table 2 provides a comprehensive comparison of various diagnostic methods, highlighting their respective strengths, weaknesses, and ideal applications in the context of railway system maintenance and monitoring.

## Wheels

In the early 1980s, Battelle-Columbus Laboratories in the United States designed a dynamic vertical wheel loads measurement system. AMTRAK installed the initial version of this system in mid-1983 along the North East Corridor to identify the vertical forces generated by train wheels. This equipment effectively pinpointed and flagged dynamic wheel loads exceeding a predefined threshold, which was caused by irregularities in the train wheels as they passed by [72]. The measurement systems were microcomputer-based and were designed for monitoring, analyzing and reporting dynamic forces between train wheels and rails. When the forces generated by passing train wheels exceeded user-defined thresholds, the system identified the axle position within the train and transmitted information via a modem link to a remote terminal, simultaneously triggering an audible alarm. The system compiled and stored statistical tables, including peak, mean, and dynamic forces, as well as peak-to-mean ratios for all passing wheels. Vertical wheel forces were measured using resistance strain gauges fixed to the web of the rail. Forces were measured at eight sequential crib locations. Each measurement circuit comprised four shear gauge pairs linked to a front-end processor responsible for recognizing and transmitting the highest force values from each successive wheel to a central computer. The central computer, in turn, identified and communicated any forces that surpassed pre-established limits while also keeping statistical records up to date. There were five available threshold levels for peak force, dynamic force, and peak-to-mean ratio. An audible alarm at the reporting destination

**Table 2.** Summarizing the key characteristics, advantages, and disadvantages of each diagnostic method

| Diagnostic method | Advantages | Disadvantages | Suitability |
|---|---|---|---|
| Track geometry measurement systems | High accuracy, detailed track profile data, suitable for preventive maintenance planning. | Expensive, requires dedicated vehicles or trackside equipment, may disrupt operations. | Regular inspections, post-maintenance evaluation. |
| In-service vehicle monitoring systems | Cost-effective, utilizes existing rolling stock, provides real-time data. | Lower accuracy compared to dedicated systems, data interpretation requires advanced algorithms. | Continuous monitoring, early detection of track irregularities. |
| Fiber optic sensors | High sensitivity, long-range monitoring, immunity to electromagnetic interference. | Relatively new technology, requires infrastructure installation, data analysis complexity. | Monitoring critical structures (bridges, tunnels), detection of internal cracks or stress. |
| Onboard monitoring systems | Continuous monitoring, real-time data on component health, fault detection and isolation. | Requires installation of sensors on various subsystems, data interpretation complexity, potential for false alarms. | Early detection of component degradation, preventive maintenance scheduling. |
| Periodic inspections | Thorough examination, allows for visual and manual checks, identification of wear and tear beyond sensor capabilities. | Time-consuming, disruptive to operations, relies on inspector expertise. | Compliance with regulations, detection of advanced failures not captured by sensors. |
| Vibration analysis | Non-intrusive, identifies issues within bearings, gears, and other rotating components. | Requires specialized equipment and expertise for data interpretation, may not pinpoint the exact location of the fault. | Monitoring component health trends, detection of developing problems. |

was activated when any combination of these thresholds was exceeded [72]

Samuels and Palesano [73] presented the statistical analyses and assessed the efficacy of a computerized detection system for determining wheel impacts on a primary rail line implemented by Conrail in 1986. Information collected from the detector was utilized to analyze the statistical characteristics of wheel impacts for various types of trains, including trailer vans, coal transports and mixed freight trains. Instances of wheel impacts surpassing specific threshold levels for dynamic incremental loads and peak impact loads were employed to identify wheel sets on railcars in need of inspection. Inspection data revealed that the utilization of dynamically measured wheel impact loads is an exceptionally efficient method for pinpointing inspection efforts toward wheel sets with a high likelihood of having condemnable defects.

In 1999, Lechowicz and Hunt [74] described a wheel impact load detector (WILD) that allowed rail and infrastructure owners to track the performance of vehicles through precise in-motion weighing, thorough analysis of load distribution and the detection and categorization of defects at the wheel, bogie, wagon and train levels.

Over 200 instances of wheel flats were intentionally created under controlled conditions and investigated by Jergéus et al. [75] in the form of on-site tests involving a moving train. The study included varying wheel loads, train speeds, sliding durations and adjustments to the friction coefficient between the wheel and rail. Samples were extracted from the affected wheel surfaces and subjected to detailed metallographic analysis to investigate phase transformations and the presence of cracks. Additionally, a numerical model for predicting wheel flats was both qualitatively validated and quantitatively fine-tuned through these experiments. The findings revealed the consistent presence of martensite beneath all flats, and cracks were observed in most cases. Consequently, it is recommended that the potential for future spalling be considered for all wheelsets with flats.

In 2001, Danneskiold-Samsøe and Ramkow-Pedersen [76] presented a wheel profile diagnostic system based on an array of accelerometers, laser scanners and cameras which, coupled with calculation algorithms, enabled the diagnosis of various defects such as wheel flats, out-of-round wheels and corrugated wheels. Substantial cost savings and potential enhancements, wheel maintenance expenses, wheel inspection costs, track maintenance expenditures, component repair costs, as well as expenses associated with noise and vibration reduction were identified.

In 2003, Johansson and Nielsen [77] explored the impact of various forms of railway wheel irregularities on the vertical dynamic forces between the wheels and the tracks, as well as the overall track response. Their investigation involved a wide-ranging set of experiments and numerical simulations. Analysis of freight trains equipped with different severe wheel tread damages, covering wheelflats, local spalls resulting from rolling contact fatigue cracking, extended local defects, and polygonal wheels was conducted. Some of the field tests considered measurements of vertical wheel-rail contact forces through a strain gauge-based wheel impact load detector. The track response was recorded using strain gauges and accelerometers on rails and sleepers. The collected data were used for calibration and validation of numerical models used to simulate the interaction between trains and tracks. The study also includes a comparison of results between a linear track model and a state-dependent track model.

In 2007, Attivissimo et al. [19] assessed real-time wheel-rail interaction quality by employing a railway measurement system. The aim of this study was to evaluate the equivalent conicity, a parameter defined by the international Union of Railways (UIC) 518 Standard. The proposed measurement system processes geometric data acquired through a contactless optical unit. The verification of this measurement system has been conducted according to the procedures outlined in the UIC 519 Standard, particularly with respect to the necessary measurement precision.

In 2011, Thakkar et al. [78] presented the investigation of acoustic emission (AE) generated during the interaction between rails and wheels. They simulated wheel defects with the aim of developing methods for diagnosing wheel flats in situ utilizing sensors mounted on the rails. A series of experiments was conducted on a scaled testing apparatus, featuring a single wheel moving along a circular track. During these experiments, AE was recorded at a fixed location on the track. The wheel had three unevenly distributed flats machined onto it, and the rolling speed and axle load varied. A previously established time-based analytical model was employed to reconstruct the typical pattern of a wheel traveling around the track. A frequency-based pulse-train model was employed to establish a method for matching the observed spectra with the expected pulse train spectra, which resembled the concept of defect frequencies in bearings. Across the full range of conditions, all the enveloped time-series data exhibited a discernible pattern of flats, which was reasonably reproducible between consecutive rotations. The authors concluded that, with appropriate calibration, the proposed method could be employed to diagnose wheel defects in actual railway wheels using either track- or wheel-mounted sensors.

Also in 2011, Wei et al. [79] presented a real-time diagnostic system that uses Fiber Bragg grating sensors to monitor wheel defects. It measures and processes the track strain response during wheel–rail interactions to generate a condition index that directly indicates the state of the wheels. This approach has been verified via extensive field tests, and the initial results indicate that this system, which is immune to electromagnetic interference, offers an effective alternative for wheel defect detection. It significantly improves maintenance management efficiency, reduces detection costs and, most importantly, helps prevent derailments in a timely manner.

In their 2014 study, Asplund et al. [80] indicated that wayside monitoring systems along the rails identify issues such as wheels exceeding defined safety limits, but can only identify such problems at specific points along the track. As a result, damage may occur on the track before the system detects faults at its location. The research team examined the wheel profile parameters measured using a wayside wheel profile measurement system installed along the rail and correlated these measurements with warning and alarm signals from a wheel defect detector installed on the same rail line. The research demonstrates that an increase in wheel wear, which can be detected through changes in the wheel profile parameters, could help reduce the risk of capacity-limiting wheel defect failures and the subsequent reactive measures.

In 2014, Papaelias et al. [81] presented a novel condition monitoring system centered around high-frequency acoustic emission and vibration analysis, which has been integrated onto a train. The diagnostic system leverages cost-effective and durable acoustic emission sensors and accelerometers, ensuring straightforward installation on the axle bearing box with minimal disruption. Empirical testing conducted in re-al-world conditions established that the developed system can detect defects associated with wheels and axle bearings.

In 2015, Asplund et al. [82] introduced a technique for evaluating the quality of data collected from a condition monitoring system designed to assess the condition of rolling stock wheels. The focus of this research was to determine whether the data meet the necessary standards for further analysis. Simultaneously, variations between measurement units within the same system were investigated and potential correlations between different measurements of wheel parameters, speed and time were identified. The evaluation of data quality was achieved through the dimension of freedom from error. Two sources of data were analyzed: an automated wheel profile measurement system and a manually operated wheel profile measurement device. The manual measurements of wheel profiles validated the accuracy of the automated wheel profile measurements. The results reveal certain inconsistencies, suggesting that this system has poor accuracy. This indicates a need for internal calibration or self-adjustment to enhance its quality.

In their 2016 study, Alemi et al. [83] proposed a wheel diameter measuring system based on WILD. With knowledge of the wheel diameter, recorded impacts were correlated with specific positions on the wheel's circumference. A novel configuration of strain sensors was proposed alongside an algorithm for data filtering and processing. A series of simulations were conducted to explore the impact of various parameters, including the number of sensors, filter thresholds, defect sizes and sensor noise. The principal outcome of this research confirms the WILD's capability for monitoring wheel diameter and its effectiveness in monitoring multiple aspects of wheel condition within a single system.

In 2018, Song and Sun [84] investigated the influence of polygonal wheels on vehicle dynamics and monitoring methods to enhance the safety and service quality of high-speed railway transportation. A measurement system that identifies wheel polygons based on wheel–rail (W/R) contact force measurements using PVDF strain sensors was established in the railroad network, demonstrating long-distance capabilities and high stability. Utilizing the W/R contact forces resulting from wheel polygon impacts, the data from the PVDF strain sensors were processed to create an indicator of wheel polygon. An automatic remote condition monitoring system was developed for use under GSM-R transmission lines. Preliminary experimental results indicated that this system is well-suited to the complex electromagnetic environment and stability requirements of high-speed railways.

Xu et al. [85] 2018 introduced a data-driven approach for monitoring the wear and tear of high-speed train wheels by utilizing onboard vibration sensors. Their method was tested using real operational data gathered from high-speed trains in China over a six-month period. The initial results demonstrated the accuracy and practical applicability of the method in real-world scenarios. A real-time wear predictive model, which was based on short-time fourier transform (STFT) and principal component analysis (PCA) using onboard vibration signals, was proposed and validated during on-tracking test trials. Strong correlation between vibration signals and the dynamic performance of the railway system was indicated, emphasizing the sensitivity of these signals with regard to predicting wear.

In 2019, Ni and Zhang [86] introduced a Bayesian statistical method for assessing wheel conditions with track-side monitoring. Data from monitoring were used to extract wheel quality-related components, and their Fourier amplitude spectra were adjusted to create a series of cumulative distribution functions that represented wheel quality characteristics. Subsequently, a data-driven reference model was established through Bayesian learning to model characteristic functions for wheels in good condition. The Bayes factor was then employed to differentiate new observations from the reference model, enabling a real-time quantitative assessment of wheel conditions. To test the feasibility and effectiveness of this approach, strain monitoring data from rail bending, collected via an optical fiber sensor-based track-side monitoring system, was implemented for validation. In 2020, Gao et al. [87] developed a diagnostic system based on a reflective optical position sensor which enabled dynamic and quantitative flat detection during high-speed train travel. The system incorporates two sensors positioned alongside the rails to assess the wheel–rail impact force throughout the wheel's entire circumference by monitoring the displacement of a collimated laser spot. To establish a quantitative relationship between the sensor readings and flat wheel length, a vehicle-track coupling dynamics analysis model was developed using finite element and multi-body dynamics methods. The model considered various factors such as train speed, load, flat wheel lengths, and impact positions to simulate their effects on impact forces, with measured data normalized based on simulation results. The system's performance was evaluated through simulations, laboratory tests, and real field trials, confirming its accuracy and practicality. This system not only identifies flat wheels but also quantifies the extent of the detected flat, offering a wide range of potential applications.

In 2021, Mosleh et al. [88] focused on wheel flats wayside monitoring system sensors with the aim of determining their optimal placement. Specific measurement points for shear and acceleration were established to explore how different sensor types (strain gauge and accelerometer) and their installation locations impact layout schemes. Using shear and acceleration data collected from 19 track positions as inputs, the presence of wheel flats was identified through the envelope spectrum approach using spectral kurtosis analysis. The research delves into the impact of sensor types and their positions on the accuracy of the wheel flat detection system.

In 2024 Chung and Lin [89] a study on wheel condition monitoring during train operation highlighted its importance in preventing unexpected events. The research involved installing piezoelectric sensors on railway tracks to collect dynamic voltage-and-strain signals generated when train wheels passed over them. These one-dimensional time series signals were transformed into two-dimensional Recurrence Plots images, which served as input data sets for two deep learning models: Xception and EfficientNet-B7. The models performed binary classification to indicate the health state of train wheels as either Normal or Faulty. The performance of the models was evaluated using five metrics: Accuracy, Precision, Recall, Miss Rate, and AUC. The findings demonstrated high classification accuracy (91.1%) for both models. However, EfficientNet-B7 outperformed Xception in terms of Recall, Miss Rate, and AUC, making it a more suitable classifier for identifying defective wheels. This research significantly contributes to train wheel condition monitoring and health management by providing effective diagnostic information for maintenance decisions, thereby reducing the occurrence of unexpected events.

## Bogies

Selinger et al. [90] presented a novel bogie designed for freight wagons with an integrated life cycle unit (LCU). This LCU enables the collection of operational data and the measurement of stress on wear components. These data can then be utilized to assess the actual lifespan of the bogie's components and streamline relevant maintenance procedures. The approach was verified with different stress cases and implemented in a testbed. In 2005, Goda and Goodall [91] presented a railway vehicle bogie suspension faults detection system based on a model estimation approach involving a Kalman–Bucy filter and an isolation scheme. The authors reported that the main advantage of the system is its ability to detect numerous faults with only a limited number of sensors. The simulations demonstrated that the Kalman–Bucy filter's residual can effectively detect suspension faults and changes in the system for railway vehicle bogies.

In 2007, Li et al. [92] presented the estimation of parameters for railway vehicle suspensions with the aim of facilitating condition-based maintenance. A simplified plan-view model of railway vehicle dynamics was presented and a Rao-Blackwellized particle filtering (RBPF) technique was employed for parameter estimation. Computer simulations were conducted to evaluate the accuracy of parameter estimation across various sensor configurations and its resilience to uncertainties related to the statistical properties of random track inputs. Their method was validated using real test data obtained from a Coradia Class 175 railway vehicle equipped solely with bogie and body-mounted sensors.

In 2009, Mei and Ding [93] presented an innovative approach to detect faults and monitor the condition of vehicle suspensions. Their method, which is based on cross-correlations between the measurements from bogie-mounted cost-effective inertial sensors, utilizes the dynamic interactions between various vehicle modes resulting from component failures. It has proven to be highly sensitive when it comes to distinguishing different fault conditions and is capable of handling complex dynamic and nonlinear systems. Although the vertical primary suspensions are the subject of this study, the authors indicated that the technique may be also applied to detect faults in lateral primary suspensions and in secondary suspensions and could possibly be extended to monitor the conditions in other dynamic systems with symmetrical configurations.

In 2010, Ward et al. [94] assessed the utilization of condition monitoring to identify suspension component status, detect low-adhesion conditions and evaluate the condition of the wheel–rail interface. The main aims of the presented research focused on generally employed techniques, inexpensive sensors and advanced filtering, which could feasibly be applied to every bogie and wheelset in a train formation. The authors investigated the possibility of developing real-time condition monitoring algorithms for safety-critical components within the rail vehicle bogie system by monitoring suspension dampers using a Rao Blackwellized particle filter and validation through network data. The authors also discussed the necessity of developing efficient algorithms which can be applied in real time, as well as the challenges related to sensor placement.

In 2010, Tsunashima and Mori [95] discussed the possibility of identifying suspension failures in railway vehicles by employing a multi-model approach with on-board measurement data. The model of the railway vehicle incorporates lateral and yaw movements of the wheelsets and bogie, as well as the lateral motion of the body. Inertial sensors were used to measure the lateral acceleration and yaw rate of the bogie, as well as the lateral acceleration of the service vehicle body. The detection algorithm was devised based on the interacting multiple-model (IMM) approach, which integrates a method for updating the estimation model. The IMM method has been employed in a simulation study for detecting faults in vehicle suspension systems. It estimates the mode probabilities and states of the vehicle suspension systems through a Kalman filter (KF). The performance of this algorithm is assessed through simulation examples, and the results demonstrate its ability to detect on-board faults in railway vehicle suspension systems under realistic conditions.

Daadbin et al. [96] (2012) focused on the monitoring of critical components in rail transportation, such as axle vibration and pantograph load. A system was designed for monitoring the transmitted torque and bending moments in the rail vehicle axle, serving as a means to identify abnormal loading. Advancement of strain gauge instrumentation, telemetry systems, and data loggers for demanding transportation applications were discussed. A rail axle stress monitoring (RASM) consisting of six data loggers, synchronized across all channels, was used, and each data logger was configured to perform both Rainflow Count (which counts fatigue or acceleration cycles) and to record the 100 highest events in the time domain. By collecting synchronized data from axle stress and axle box acceleration, stress occurrences can be associated with vehicle operation, allowing the investigation of dynamic interaction between the wheels and the rail.

In 2016, Amini et al. [97] presented the outcomes of high-frequency acoustic emission measurements conducted on freight rolling stock in Long Marston UK. Intentional damage was induced in axle bearings and acoustic signals were recorded during lab and field testing. Passive high-frequency resonant piezoelectric acoustic emission transducers and time spectral kurtosis were employed for acquisition and analysis of the acoustic emission data. The results demonstrated that time spectral kurtosis can effectively distinguish axle bearing defects from the background noise generated by various sources, such as the wheel–rail interaction, braking and changes in train speed. Extraneous noises, e.g., noises caused by the braking system, can increase the RMS value and cause a slight increase in kurtosis, potentially leading to false defect identifications. The authors demonstrated that using time spectral kurtosis, which incorporates time and frequency domain information, significant enhancement in the ability to detect bearing defects was observed in such scenarios.

Los Santos et al. [98] (2017) investigated the rate at which surface defects in railroad bearings, specifically spalls, grow per mile of full-load operation. The presented data were gathered from defective bearings subjected to various load and speed conditions using specialized railroad bearing dynamic test rigs operated by the University Transportation Center for Railway Safety (UTCRS) at the University of Texas Rio Grande Valley (UTRGV). Periodic removal and disassembly of these railroad bearings was carried out to inspect and measure the size of defects at the outer ring (cup). Castings of spalls was introduced using low-melting, zero-shrinkage Bismuth-based alloys to record and investigate spall geometry. Spalls were measured using optical techniques combined with digital image analysis, as well as manual coordinate measuring instruments. The study determined the spall growth rate in terms of area per mile of full-load operation. Initially, the size of spalls was randomly distributed, depending on the originating defect's depth, size, and location on the rolling raceway. The surface spalls had two distinct growth regimes, with an initial slower growth rate that accelerated once spalls reached a critical size. While there was significant variability, upper and lower bounds for spall growth rates were proposed, and the critical dimension for the transition to rapid spall growth was estimated. A preliminary model for spall growth was defined for the purpose of initial detection of bearing spalls with condition monitoring tools.

In 2018, Li et al. [99] presented a concept of an onboard health monitoring system tailored for heavy haul wagons. Their system encompasses a signal-based fault detection and isolation (FDI) method along with a real-time fault diagnosis approach. The proposed monitoring system implements two accelerometers, which are positioned on the front left and right rear of each car-body within a heavy haul train to detect faults in the bolster springs. The authors investigated the impact of these faults and their detectability by conducting simulations on straight and curved tracks, utilizing a model of a heavy 40 ton axle load haul wagon. The simulation results were analyzed and compared using cross-correlation techniques, leading to the proposal of a fault detection and isolation system which introduces five potential fault indicators, demonstrating the feasibility of detecting changes in bolster stiffness within a range of ± 25%.

In 2019, Chudzikiewicz et al. [100] presented the process of selecting specific points on a rail vehicle to record signals intended for monitoring the vehicle's condition, especially the first and second-degree suspension system elements. Initially, seven possible points for signal registration on a rail vehicle were defined and subsequently reduced to four. The statistical measures used to evaluate the suitability of recorded signals were defined. Practical implementation of a prototype system on the ED74 type rail vehicle confirmed the validity of the initial assumptions and enabled an assessment of the defined diagnostic indicators.

In 2019, Tarawneh et al. [101] indicated that rolling contact fatigue (RCF) was a significant factor behind the failure of railroad bearings used in freight service. The authors' primary aim was create dependable prognostic models for spall growth in railroad bearings based on actual service life testing. The data used for these models came from laboratory and field tests. Empirically observed spall growth patterns in both the inner and outer rings of bearings, even when subjected to varying conditions such as speed, load, and temperature, indicate that a straightforward empirical model for spall area expansion can serve as the basis for predicting the remaining useful life of a bearing when a spall is detected.

In 2020, Sánchez et al. [102] presented a method for evaluation of condition indicators for railway axles crack detection in condition-based monitoring. Authors assessed the vibration signals captured by accelerometers placed along the longitudinal direction and implemented data fusion technique, involving the evaluation of six accelerometers and the merging of condition indicators based on sensor placement. Fifty-four condition indicators were calculated for each vibration signal, with the best features selected using the Mean Decrease Accuracy method of Random Forest. The chosen indicators were tested using a K-Nearest Neighbor classifier. A real bogie test bench was utilized to simulate crack faults in railway axles, with vibration signals measured on both the left and right sides of the axle. Tests highlighted the performance of condition indicators and demonstrated the effectiveness of fusing condition indicators for crack fault detection in railway axles.

In 2022, Zanelli et al. [103] proposed a wireless monitoring system designed for diagnosing freight train brake systems. Their system incorporates a low-power architecture that focuses on energy harvesting and wireless communication and allows for the collection of brake pressure data at critical points to verify the system's operation parameters. The study also presents experimental results obtained during a five-month field test over a distance of more than 24.000 km on significant rail routes across Europe.

A 2024 Guo et al. [104] study aimed to improve evaluation criteria for hunting stability in high-speed trains by developing a method to identify small-amplitude bogie hunting (SABH) motion. Using labeled field-measured bogie lateral acceleration data categorized as normal and SABH, the study identified harmonic character-related features, like the autocorrelation coefficient and approximate entropy, as crucial for SABH identification. The decision tree classifier outperformed others, including support vector machine and naive Bayes. Sensitivity analysis confirmed the method's effectiveness with a sampling frequency of 50–200 Hz and a window length of 5–10 seconds. This research provides valuable insights for developing improved monitoring and control systems to address hunting instability in high-speed trains.

### Locomotive systems

In 1989, Appun and Daum [105] discussed the problem of high-power and high-speed three-phase traction drive systems' external and internal diagnostic methods. The authors described external diagnostic methods and established several less expensive methods that did not require installing equipment on the vehicle. The authors stated that external diagnostic methods are primarily suitable for maintenance rather than operational diagnosis, and employed mainly for specific cases, such as testing objects with limited scope and complexity. Further attention has been directed towards internal diagnostic equipment integrated into the vehicle, as well as potential self-diagnostic capabilities. They also presented typical applications of internal diagnostic systems that have already been field-tested.

In 1995, Daley et al. [106] presented an overview of several rail vehicle traction and braking systems fault diagnosis methods spanning from classical condition monitoring to advanced model-based techniques. According to the authors, FDI techniques promise to yield several benefits, such as decreased maintenance needs, improved service availability and enhanced safety. Schemes for fault-tolerant traction motor torque control, which rely on innovative state variable observers, were proposed. The Implementation of the bilinear state space observer was reported as a feasible way to simultaneously estimate unmeasured states and isolate faults in up to two sensors with minimal computational overhead. Simulations of fault detection schemes illustrated the potential benefits of the proposed approach.

In 1997, Winterling et al. [107] analyzed the dynamic load conditions for traction drives. Fault conditions within the electrical drive were reported in peak torques or trigger oscillations that might potentially harm the mechanical drive. To address this concern, models of traction drives, encompassing components such as power converters, motors, mechanical drives and wheel-rail contact, were devised to replicate drive operation under fault conditions. The authors reported that simulating fault scenarios in electrical drives is essential for designing an electromechanical traction system that can operate without damaging its mechanical components. The most challenging conditions were observed when the stator operated at its highest frequency with rated flux and torque while running on dry rails.

Deuszkiewicz and Radkowski [108] (2002) investigated diagnostic parameters and methods for classifying the condition of a power transmission unit within a commuter train. The axle box of the vibrations and track vibrations were analyzed, both before and after undergoing repairs. The diagnostic method combined diagnostic parameters derived from the signal itself and its envelope and proved to be suitable for online procedures. Despite the relatively minor wear and tear on the rolling bearings, the produced signals provided valuable insights into the overall unit's condition. Experiments revealed that different power transmission units exhibited distinct individual characteristics, and the proposed algorithm could effectively differentiate between them. An algorithm used to identify an object's technical condition using neural networks and online diagnostic system was presented.

In 2008, Kia et al. [109] introduced a scaled experimental platform designed for the advancement of railway traction monitoring methods. The proposed sensor system was intended to establish a clear understanding of electromechanical interactions, facilitating the investigation of mechanical monitoring techniques using Motor current signature analysis (MCSA). A downsized experimental setup in the form of a test-bed traction bogie served as an initial evaluation stage for studying the typical electromechanical properties of a traction system and establishing the fundamental relationships between mechanical and electrical phenomena. Due to the non-stationary nature of railway traction systems, conventional signal processing methods were found not suitable for intensive use. Therefore, proposed time-frequency signal processing techniques should offer a more dependable approach to analyzing crucial mechanical components within a traction system. Later this year, the same authors proposed the application of non-invasive measurements for estimating electromagnetic torque as a means of monitoring mechanical torsional stresses in an induction machine drive system operating under non-steady conditions [110]. An experimental setup involving a 5.5 kW squirrel-cage induction machine connected to a one-stage gearbox was employed to validate the approach. The authors stated that estimation of electromagnetic torque can provide valuable insights into the operational health and effectiveness of an electromechanical system. This study implemented this method to analyze torsional vibrations in a gearbox under nonstationary condition, as well as the longevity of shafts, bearings and gearboxes in electromechanical systems. The design, development and test results of the first fully proven Pantograph Monitoring System, which was regularly used on trains in the UK, was presented in 2012 alongside a Rail Axle Stress Monitoring system created by Daadbin et al. [94]. The Pantograph Damage Assessment System (PANDAS) described in this paper is in regular use on the Class 390 "Pendolino" tilting trains operating on the West Coast Main Line (WCML) in the UK. This system has received Network Rail approval and is being rolled out nationwide.

## CONCLUSIONS

In conclusion, the field of railway diagnostics continues to evolve with advances in sensor technology, data analytics, and communication systems. Each diagnostic method—whether it's track geometry measurement systems, in-service vehicle monitoring, fiber optic sensors for infrastructure, or onboard monitoring systems for rolling stock—brings unique advantages and challenges to ensuring the safety and efficiency of railway operations. Track geometry measurement systems offer high accuracy and detailed data for preventive maintenance planning but come with significant cost and operational disruption considerations. In-service vehicle monitoring systems leverage rolling stock for cost-effective, real-time monitoring, yet require sophisticated algorithms for data interpretation. Fiber optic sensors provide sensitive, long-range monitoring capabilities but entail high initial costs and complex data analysis. Similarly, onboard monitoring systems facilitate continuous, real-time monitoring of rolling stock health, enabling early fault detection and maintenance scheduling, while periodic inspections remain essential for comprehensive checks and regulatory compliance, despite their time-consuming nature and potential operational disruptions. Vibration analysis offers non-intrusive insights into component health trends but requires specialized expertise for accurate interpretation. Looking forward, the integration of multiple sensor technologies, advanced data analytics, and wireless communication systems holds promise for the reliability, safety, and cost-effectiveness of railway operations. By addressing current challenges and leveraging emerging technologies, railway operators can achieve more efficient maintenance practices, predictive capabilities, and improved overall performance, ensuring sustainable and optimized railway transport systems for the future.

Research on bogies, suspension systems, and other less researched components is crucial for enhancing the safety and efficiency of railway systems. These components play a fundamental role in the overall performance and reliability of trains. Bogies, for instance, are essential for ensuring smooth and stable rides by housing the wheels and axles, and facilitating the train's maneuverability on tracks. However, due to wear and tear, they are susceptible to issues like axle fractures and bearing failures, which can lead to derailments and significant safety hazards. Similarly, suspension systems are vital for absorbing shocks and vibrations, providing a comfortable ride for passengers and reducing stress on the track infrastructure. Failures in the suspension system can result in uncomfortable rides, increased wear on the tracks, and even derailments in severe cases. Despite their importance, these components often receive less research attention compared to more visible elements like locomotives and power supply systems.

Our literature review demonstrates that railway diagnostic and fault detection research is gaining momentum. There has been a clear increase in the number of research papers on this topic since 2012. The greater part of the research on diagnostic systems and fault detection in railway systems focuses on track or wheels, with track accounting for approximately 58% and wheels for approximately 17% of the analyzed works. Boogies and suspension systems of locomotives and fright wagons, brake systems, rail vehicle axles and bearings are the subject of some research papers, but not to the same extent, rendering this an underexplored topic with many potential research opportunities.

New research agendas focus on sophisticated digital signal processing techniques, simplification of data acquisition systems in regards of sensor count and placement. as well as the reduction of continuously recorded data weight. Accelerometers and inertial sensors are commonly used in railway diagnostic systems as they provide robust data that are easy to process. Visual techniques, alongside acoustic and fiberoptic measurements, are mentioned in the literature, but not the same extent as the previously mentioned inertial sensors. Big data and machine learning techniques, coupled with properly chosen sensor and sensor placement, can collect vast amounts of useful data; thus, they have been identified as the optimal approach to diagnostic problems in railway systems, for both infrastructure and rolling stock.

In the realm of railway diagnostics, significant progress has been made through various methodologies and technologies aimed at enhancing the safety, reliability, and efficiency of railway systems. However, several gaps remain that present opportunities for future research and development.

One major area for future research is the integration of advanced data analytics and machine learning algorithms into railway diagnostic systems. Current methods generate vast amounts of data that are often underutilized. By employing sophisticated data analytics and machine learning techniques, it is possible to enhance the accuracy and predictive capabilities of fault detection systems. This can lead to more effective predictive maintenance strategies, reducing the occurrence of unexpected failures and optimizing maintenance schedules.

Another key direction is the development of wireless sensor networks (WSNs). While traditional wired sensors provide accurate data, they are often limited by their physical connectivity requirements. WSNs offer a flexible and cost-effective solution, especially useful in monitoring remote or hard-to-access areas of the railway infrastructure. These networks can enhance real-time monitoring capabilities, allowing for continuous data collection and analysis without significant disruption to railway operations. Furthermore, research into robust cybersecurity measures is crucial, given the increasing digitization and interconnectivity of diagnostic systems. Ensuring the security of these systems from cyber threats is essential to maintain the integrity and reliability of railway operations.

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