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Review

A Systematic Review and Unified Framework for Predictive Maintenance in the Railway Domain

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Abstract

Predictive maintenance has become an important strategy for improving asset reliability and safety, particularly with the increasing integration of artificial intelligence (AI) into maintenance processes. In the railway domain, where maintenance activities can account for up to 40% of the overall budget allocated across the V-cycle of rolling stock development, the adoption of smart maintenance strategies is increasingly important. However, an integrated understanding of predictive maintenance approaches across the railway domain remains lacking. This study provides an in-depth review of predictive maintenance research in the railway domain through a PRISMA-guided systematic search of three major scientific databases: Scopus, Web of Science, and ScienceDirect. A total of 61 full-text articles were retained and analyzed in detail. The reviewed studies are synthesized according to their methodological approaches, namely data-driven, model-based, and hybrid approaches, and their distribution across railway subsystems is examined. The analysis reveals a concentration of research on rolling-stock components, particularly wheelsets and switch machines, while comparatively less attention is devoted to less-instrumented but similarly safety-critical assets, such as traction, signaling, and door systems. Based on these findings, a conceptual hybrid predictive maintenance framework is proposed by synthesizing the approaches identified in the literature. Finally, the study highlights key research challenges and identifies open research questions and future research directions, including the need for more comprehensive, subsystem-specific, and practically validated predictive maintenance solutions.

Keywords: predictive maintenance; remaining useful life; railway domain; machine learning; artificial intelligence

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1. Introduction

Maintenance has long been recognized as a critical activity across numerous industries [1], particularly in safety-critical sectors such as aeronautics, space, railway, and automotive systems. The appropriate selection of a maintenance strategy can significantly reduce operational costs [2], minimize service disruptions [3], and improve productivity and asset remaining useful life [4]. In both academia and industry, maintenance strategies are generally classified into two main categories: corrective and preventive maintenance [5,6]. Corrective maintenance is performed after fault detection to restore equipment to an operational state and may be either immediate or deferred depending on the equipment condition and operational requirements [7]. Preventive maintenance aims to reduce

the likelihood of failure through planned interventions and includes systematic, condition-based, and predictive maintenance (PdM). These maintenance types and strategies are illustrated in Figure 1.

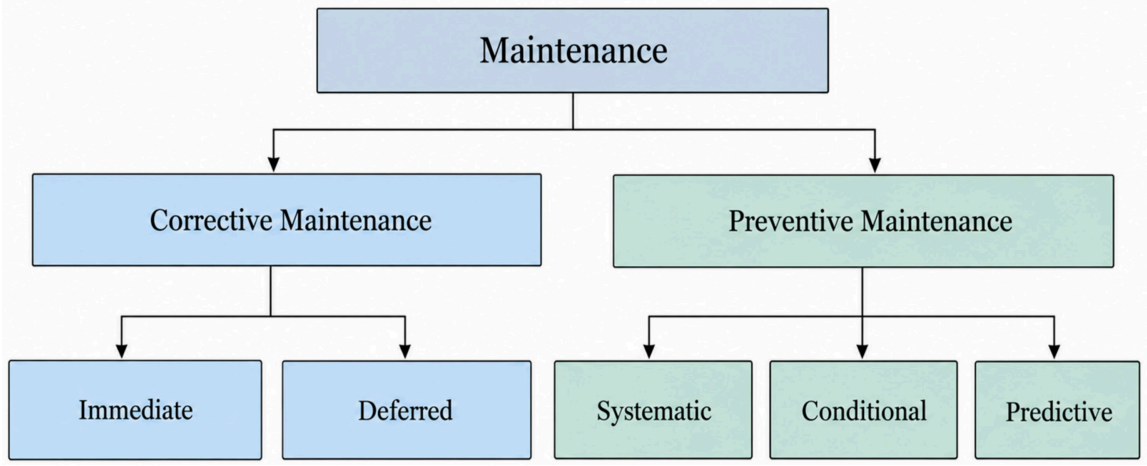


Figure 1. Maintenance types and strategies.

Predictive maintenance (PdM) has emerged as an important strategy within the fourth industrial revolution. According to [7] the European standard EN 13306 (2010), it is a form of condition-based maintenance supported by forecasts derived from the analysis of degradation-related parameters. PdM enables the early detection of abnormal conditions and potential failures by monitoring equipment health and estimating its remaining useful life (RUL) [8]. Several PdM approaches have been reported in the literature [9–12] and can be broadly classified into model-based, data-driven, and hybrid methods. Model-based approaches rely on mathematical, physical, or experience-based models, whereas data-driven methods exploit operational and condition-monitoring data to develop predictive models; hybrid approaches combine both strategies. RUL is a key parameter in equipment health management and condition monitoring [13,14], as it provides an estimate of the remaining operational life of an asset [15] and supports failure prevention and the development of predictive maintenance frameworks [16].

In the railway industry, effective maintenance is essential for ensuring operational availability and safety while controlling life-cycle costs [17]. According to Reliability, Availability, Maintainability, and Safety (RAMS) principles, maintenance is a fundamental component of railway system safety and reliability and contributes to preventing potentially severe operational consequences [18–20]. However, the large number of heterogeneous and safety-critical railway assets, together with varying operating conditions and degradation mechanisms, makes timely fault detection and maintenance decision-making particularly challenging. In this context, predictive maintenance offers significant potential by enabling continuous condition monitoring, early fault detection, failure prediction, and more informed maintenance scheduling. Recent advances in artificial intelligence (AI) and data-driven techniques have further strengthened these capabilities in railway applications [21,22]. For instance, ref. [23] developed an AI-based approach combining classification and anomaly detection to improve the reliability of railway radio communication systems, while ref. [24] demonstrated the potential of AI for predictive maintenance in hybrid and electric rail systems through real-time fault prediction and adaptive maintenance planning. Also, in the context of predictive maintenance, the most extensively studied systems include the catenary [25], HVAC system [26] and wheel bearing [27]. An overview about train components could be found on [28].

Despite the growing body of research on predictive maintenance, its application across railway systems remains fragmented across different assets, data sources, algorithms, and predictive objectives. The rapid development of AI and data-driven techniques, particularly in recent years, has further increased the diversity of methodological approaches used for railway condition monitoring and prognostics. Consequently, researchers and practitioners still lack a consolidated view of which predictive maintenance approaches, railway subsystems, and algorithms have been most extensively investigated and which areas remain underexplored. Addressing this gap, the present paper reviews recent research on predictive maintenance for railway systems, synthesizing the state of the art to identify established practices, persistent research gaps, and promising directions for future development.

This work aims to shed light on predictive maintenance and its recent methods and approaches for real-world application in the railway domain. The following research questions are addressed:

RQ1: *What algorithms and methodological approaches (data-driven, model-based, and hybrid) have been employed for predictive maintenance in the railway domain that cover rolling stock for passenger transportation (metro, TGV, RER) but also freight transportation over the past two decades, and how has their relative prevalence evolved?*
RQ2: *Which railway subsystems and components have received the greatest research attention, and which remain underexplored relative to their operational and safety criticality?*
RQ3: *What are the respective strengths, limitations, and data requirements of the three major methodological families identified?*
RQ4: *What key challenges currently limit the transition from component-level predictive maintenance research to deployable, fleet-level maintenance decision-making?*
RQ5: *How can the insights drawn from the reviewed literature be consolidated into a unified hybrid predictive maintenance framework, and what directions should future research prioritize to address the gaps identified?*

The remainder of this paper is organized as follows: Section 2 defines the methodology adopted and the related work; Section 3 presents the results of the quantitative analysis; Section 4 presents the qualitative analysis, detailing the algorithms and techniques identified and the railway subsystems addressed. Section 5 presents a consolidated and unified hybrid framework for the application of PdM. Section 6 discusses the findings and concludes the paper, outlining directions for future work.

2. Methodology

Systematic mapping studies (SMS) are designed to provide an overview of a research domain and typically serve as a preliminary phase preceding a systematic review [29], the latter being a comprehensive and structured examination of the existing literature on a specific topic or research question [30]. To conduct the present state-of-the-art analysis, the general steps of SMS and systematic literature review (SLR) methodologies were combined into the following process: definition of research questions, search for relevant articles, screening of papers through the application of inclusion and exclusion criteria, and paper analysis with data extraction [31]. These steps constitute the key phases of the PRISMA method.

2.1. Selection Process

The search for relevant publications was conducted across established scientific databases. The most widely used electronic sources for scientific and engineering research are Scopus, ScienceDirect, and Web of Science, each offering a range of search options. Table 1 outlines the search strategy applied to each database. To identify relevant

publications, searches were conducted within the article title, abstract, and keywords for Scopus and ScienceDirect, whereas for Web of Science, the search was performed across all fields.

Table 1. Search methodology per database.

Electronic Database	Search Within
Scopus	"Article title, abstracts, keywords"
Science Direct	"Article title, abstracts, keywords"
Web of Science	"All fields"

2.2. Search Query Construction

This step involves the definition of a search string designed to scan the databases and capture all potentially relevant studies addressing the research problem of this paper. To this end, keywords were defined and combined using the Boolean operators "AND" and "OR" to construct search strings that limited, as far as possible, the number of retrieved papers to those most relevant. The following keywords were combined to build the general search string presented in Table 2:

- "Predictive maintenance" AND
- "Railway" OR
- "Rail industry" OR
- "Rolling stock" OR
- "Train"

Table 2. Search string for paper screening.

Search String
(("Predictive maintenance") AND ("Railway" OR "rolling stock" OR "rail industry" OR "Train")

2.3. PRISMA Method

The article selection process followed the PRISMA 2020 guidelines and comprised the following phases: definition of research questions, search for relevant articles, screening of papers through the application of inclusion and exclusion criteria, and paper analysis with data extraction. Systematic database searches were conducted using the queries outlined in Table 2. Following retrieval, duplicate records were systematically identified and removed. The remaining records were then assessed against the following inclusion and exclusion criteria:

- Papers published in English.
- Papers published between 2006 and 2026.
- Peer-reviewed journal articles or conference papers.
- Papers published as open access.
- Papers that directly addressed PdM in railway.

Figure 2 presents the sequential phases of the article selection process in accordance with the PRISMA guidelines.

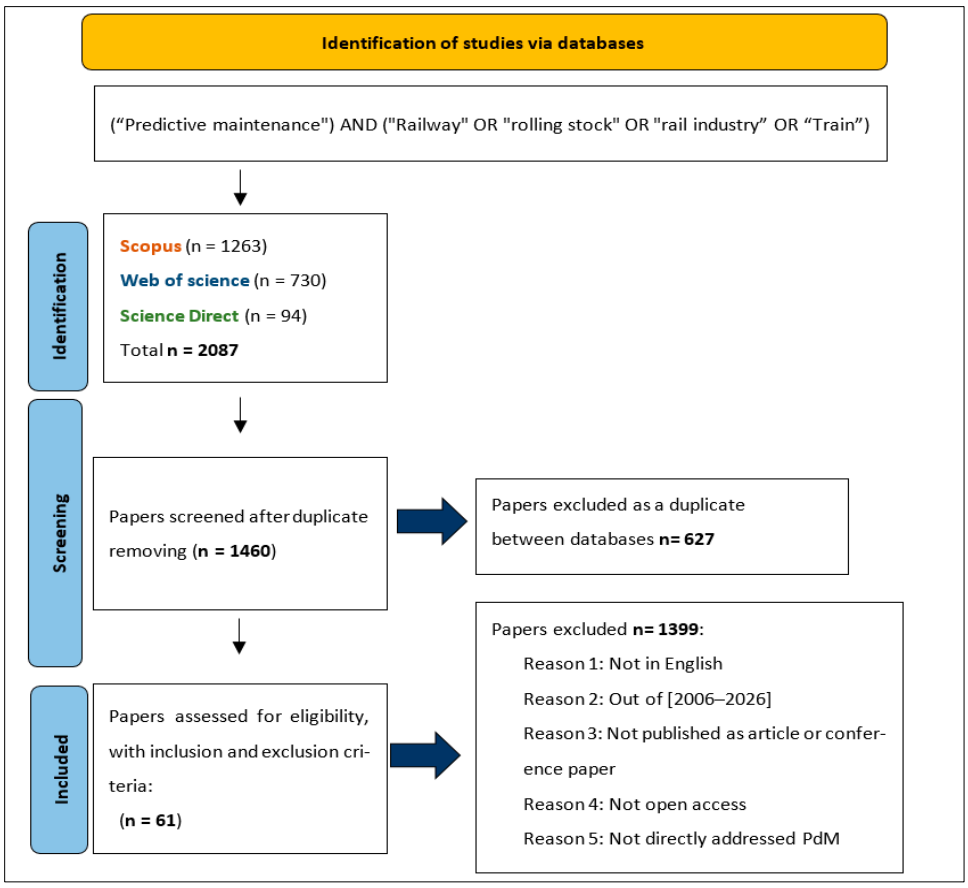


Figure 2. PRISMA method flowchart.

2.4. PRISMA Compliance and Registration

This systematic review was designed, conducted, and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement. The completed PRISMA 2020 checklist is provided as Supplementary Material, and the study selection process is reported in the PRISMA 2020 flow diagram Figure 2.

This review was not registered, and a review protocol was not prepared and published in advance. PROSPERO, the principal prospective register for systematic reviews, accepts registrations only for reviews with health-related outcomes; as the present review addresses the latest advances in the predictive maintenance of railway assets, it falls outside the scope of that register, and no equivalent mandatory registry currently exists for systematic reviews in the transport engineering domain.

The completed PRISMA 2020 checklist is available as Supplementary Material alongside this manuscript.

3. Quantitative Analysis

Figure 3 shows the results obtained using the search queries described above. Research on predictive maintenance applications within the railway sector remains comparatively limited relative to other domains such as manufacturing, aeronautics, or the automotive industry. In Scopus alone, over 17,603 papers were retrieved when the search string was restricted to "predictive maintenance," without "railway" or its synonyms. When the full search string was applied, 1263 works were retrieved from Scopus, 730 from Web of Science, and 94 from ScienceDirect, yielding a total of 2087 documents, of which more than 50% originated from Scopus.

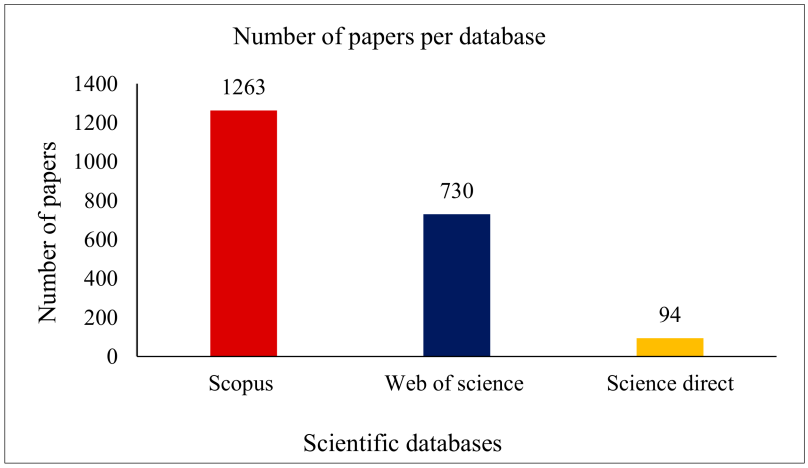


Figure 3. The number of articles per database.

Research activity in this area has intensified markedly over the past decade, as shown in Figure 4, which illustrates the yearly evolution of publications on predictive maintenance between 2006 and 2026. Between 2006 and 2016, the number of papers remained low and relatively stable, varying between 0 and 15 per year, indicating limited research activity in this field during that period. A significant increase is observed after 2016, reaching up to 79 papers published in 2021. This growth was driven by advances in data-driven technologies, including deep learning and machine learning algorithms, which enable the detection of anomalies and the prediction of failures before they occur, as well as by the emergence of IoT-enabled smart sensors that allow real-time monitoring of critical railway components. Publication numbers remained relatively stable between 2021 and 2022, likely reflecting publication delays associated with the COVID-19 pandemic. Since 2022, publication output has continued to grow exponentially, with over 305 articles published in 2025 and 236 in the current year (2026), suggesting a projected total of more than 400 papers by year-end.

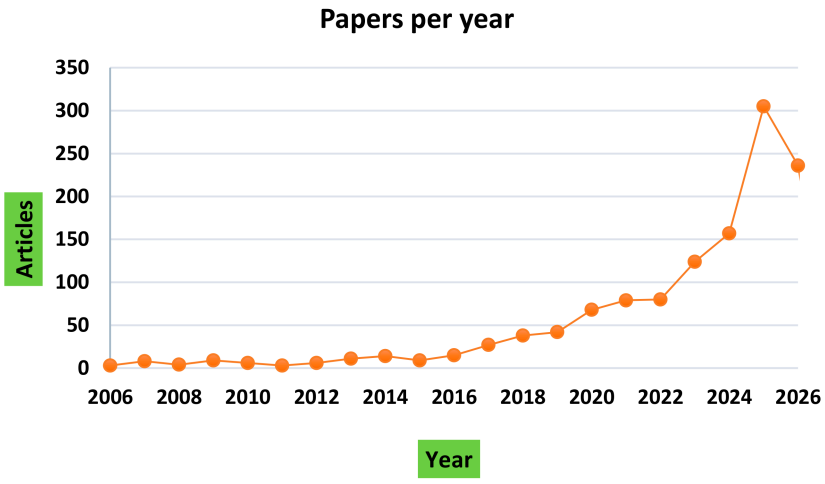


Figure 4. Number of publications per year in Scopus.

Figure 5 presents the distribution of papers by publication type in the Scopus database. The majority of documents are conference papers (46%) and journal articles (44%), whereas book chapters (3.6%) and review papers (3.5%) are considerably less represented, reflecting limited efforts to synthesize existing knowledge. Minor categories, such as books (0.4%), data papers (0.2%), and conference reviews, further underline the field's current emphasis on original research rather than on secondary or reference literature. Overall, these results

reveal a notable scarcity of review articles that summarize and synthesize research trends: among the 1263 documents retrieved from Scopus in the initial automatic search, only 44 were published as review articles, corresponding to fewer than 4% of the total.

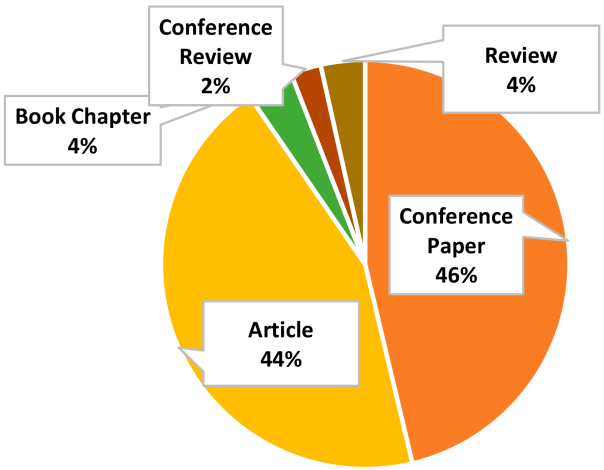


Figure 5. Paper types collected from Scopus.

The collected papers were published across numerous journals and international conferences; the five most frequent publication venues are presented in Figure 6. Applied Sciences (Switzerland) is the leading source, accounting for 30 papers, followed by Lecture Notes in Mechanical Engineering (26 papers) and Lecture Notes in Networks and Systems (22 papers). Sensors and IEEE Access complete the top five, contributing 21 and 19 papers, respectively. Together, these five venues account for 118 of the papers retrieved during the search process.

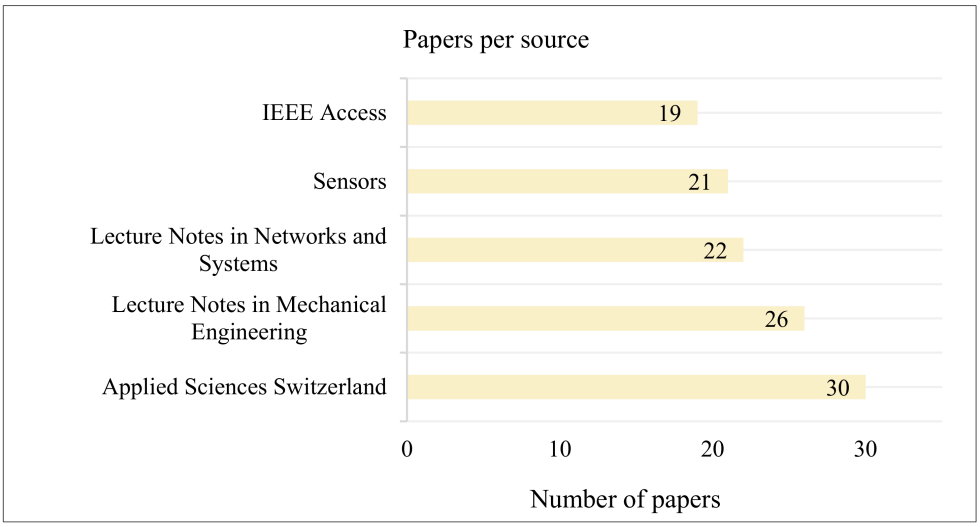


Figure 6. Papers per journal.

Among the corpus of 1085 papers assessed for eligibility against the inclusion and exclusion criteria, a wide range of keywords was employed to capture thematic relevance. Table 3 presents the fifteen most frequently used keywords, together with their respective occurrence frequencies, offering a comprehensive overview of the thematic correlations across the search domains.

Table 3. Keyword frequency analysis.

Keyword	Occurrence
Predictive Maintenance	929
Railroads	381
Railroad Transportation	357
Machine Learning	284
Learning Systems	253
Maintenance	201
Machine-learning	197
Fault Detection	178
Condition Monitoring	150
Deep Learning	134
Forecasting	125
Rails	120
Anomaly Detection	105
Artificial Intelligence	102

This keyword frequency distribution highlights the progressive integration of artificial intelligence methods into predictive maintenance within the railway sector. The predominance of the term "Predictive Maintenance" underscores its centrality as both a research focus and an operational priority. Traditional maintenance approaches are increasingly being supplanted by data-driven methods (ML, DL, and AI), which enable sophisticated fault detection, condition monitoring, and anomaly detection, all of which are critical for anticipating failures before they occur. The prominence of the keyword "forecasting" reflects the sector's shift toward proactive asset management, aimed at reducing downtime and optimizing resource allocation. Moreover, the high occurrence of "railroad transportation" and "rails" indicates that predictive maintenance is not confined to rolling stock but extends to infrastructure, where continuous monitoring is essential to ensuring safety and efficiency. Collectively, these results illustrate the evolution from reactive and preventive strategies toward algorithm-driven predictive maintenance.

4. Qualitative Analysis

This section presents the qualitative synthesis of the reviewed literature. For this stage of the analysis, 61 open-access, peer-reviewed papers directly relevant to predictive maintenance in the railway domain were selected and examined in depth.

4.1. From Traditional to Smart Approaches

The emergence of Industry 4.0, artificial intelligence (AI), and the Internet of Things (IoT) has significantly shaped the methodologies developed over the past decade. Figure 7 shows that data-driven methods have been the most widely adopted approach among the collected articles, employed in over 80.3% of the studies, whereas 3.3% relied on purely model-based approaches and 16.4% proposed hybrid models combining data-driven and model-based techniques to build a predictive mechanism. The choice of method varied across studies according to the specific case study and the resources available to the authors.

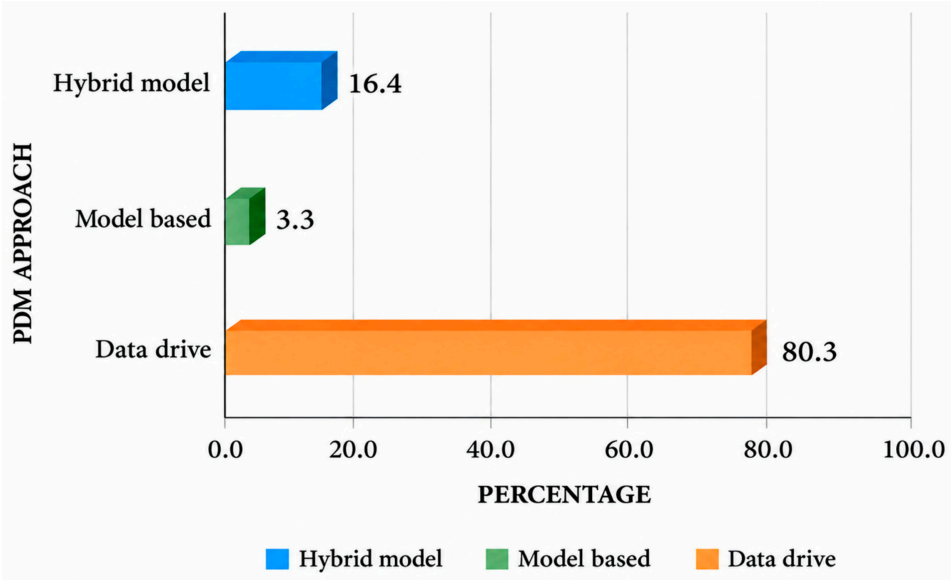


Figure 7. Distribution of predictive maintenance approaches.

4.2. Algorithms and Techniques

Table 4 summarizes the data gathered from the reviewed articles, providing a chronological overview of the methodological approaches and algorithms employed. The analysis reflects the growing adoption of data-driven approaches and machine learning techniques: approximately 80.3% of the reviewed studies rely on purely data-driven methodologies that directly exploit operational and sensor data, while a smaller but increasing number employ hybrid models combining machine learning with probabilistic or stochastic modeling to enhance robustness and generalization. Machine learning dominates the methodological landscape, with supervised techniques such as artificial neural networks, support vector machines, and support vector regression widely used for prediction and RUL estimation, and unsupervised methods such as K-means clustering applied for anomaly detection and degradation-pattern identification. Traditional statistical techniques, such as spectral and kurtosis analysis, remain present in earlier studies, illustrating the transition from classical methods toward more sophisticated AI-based models.

Table 4. Predictive maintenance approaches and methods.

No.	Ref.	Year	Approach	Methods	Algorithms
1	[32]	2024	Hybrid model	Machine Learning	Stacking ensemble with Bayesian optimization
2	[33]	2023	Data-driven	Statistical methods	Statistical prognostics model for fleet scheduling
3	[34]	2023	Data-driven	ML unsupervised	K-means clustering (DTW)
4	[35]	2022	Data-driven	Deep learning: supervised	Artificial neural network
5	[36]	2022	Data-driven	Stochastic method	Hidden Markov Model
6	[37]	2021	Hybrid model	Physics-based simulation	With Boosted Trees ensemble
7	[38]	2020	Data-driven	Deep learning	Feed-forward artificial neural network
8	[39]	2020	Data-driven	Statistical method	Spectral and kurtosis analysis
9	[40]	2020	Data-driven	Deep learning	Generative Adversarial Network

Table 4. *Cont.*

No.	Ref.	Year	Approach	Methods	Algorithms
10	[41]	2020	Data-driven	Review	Comparison of data-driven prognostics models
11	[42]	2018	Hybrid model	ML unsupervised	K-means clustering algorithm
12	[43]	2017	Data-driven	Stochastic method	Dynamic Bayesian Networks
13	[44]	2015	Data-driven	ML supervised	Online Support Vector Regression
14	[45]	2024	Data-driven	Deep learning	LSTM neural network
15	[46]	2022	Hybrid model	Deep learning	Artificial neural network
16	[47]	2023	Data-driven	Deep learning	Long Short-Term Memory
17	[48]	2022	Data-driven	ML supervised	Similarity-based models (hash, pairwise)
18	[49]	2020	Data-driven	ML supervised	Generic supervised machine learning algorithms
19	[50]	2019	Data-driven	Stochastic method	Anomaly detection and prognostics techniques
20	[51]	2020	Model-based	Stochastic method	Proportional Hazard Model
21	[52]	2020	Data-driven	Deep learning	Artificial neural network
22	[53]	2018	Hybrid model	Physics models	Monte Carlo simulation
23	[54]	2023	Data-driven	ML supervised	Change point detection and regression
24	[55]	2021	Data-driven	Digital Twin	Digital Twin with real-time operational data
25	[56]	2023	Data-driven	Machine learning	Anomaly detection techniques
26	[57]	2025	Hybrid model	NA	Systematic review of hybrid PdM models
27	[58]	2024	Hybrid model	Stochastique methods	Stocon-linear diffusion, Brownian motion
28	[59]	2025	Hybrid model	Deep learning	Hybrid LSTM-autoencoder architecture
29	[60]	2020	Data-driven	ML supervised	Machine learning-based prognostics estimation methods
30	[61]	2024	Hybrid model	ML supervised	Prognostics-based scheduling optimization (MILP)
31	[62]	2021	Data-driven	ML and DL	Time-series anomaly detection
32	[63]	2022	Data-driven	NA	Review of ML methods for track degradation
33	[64]	2022	Data-driven	ML supervised	Artificial neural network model
34	[65]	2023	Data-driven	Other	Review of vehicle-based condition monitoring
35	[66]	2021	Data-driven	NA	Bibliometric review of condition monitoring methods
36	[67]	2023	Data-driven	NA	Review of wayside condition-monitoring technologies
37	[68]	2022	Data-driven	Deep learning	Model (OORNet, CNN-based)
38	[69]	2022	Data-driven	Deep learning	Transformer-based wear prediction
39	[70]	2019	Data-driven	Deep learning	1D CNN, residual learning
40	[71]	2025	Data-driven	Machine Learning	Online continual and transfer learning

Table 4. *Cont.*

No.	Ref.	Year	Approach	Methods	Algorithms
41	[72]	2022	Data-driven	Machine Learning	Fuzzy classifier for pantograph–catenary
42	[73]	2017	Data-driven	Deep learning	Arc detection model
43	[74]	2017	Data-driven	ML	Image processing-based tracking method
44	[75]	2020	Data-driven	Stochastic	Wiener-process wear model
45	[76]	2024	Data-driven	Deep learning	Deep reinforcement learning
46	[77]	2023	Data-driven	Deep learning	Deep learning: CNN with SVDD classification
47	[78]	2024	Data-driven	Machine Learning	Multi-sensor fusion tensor machine
48	[79]	2024	Hybrid model	NA	Expert system with Bayesian network diagnosis
49	[80]	2023	Data-driven	DL	Deep learning: deep random forest fusion
50	[81]	2025	Data-driven	Machine Learning	Diagnosis approach for switch systems
51	[82]	2026	Data-driven	Machine Learning	Wavelet packet decomposition, Relief selection
52	[83]	2023	Data-driven	NA	Review of point-machine fault detection
53	[84]	2023	Data-driven	NA	General data-driven predictive maintenance framework
54	[85]	2023	Data-driven	Machine Learning	Online machine learning pipeline
55	[86]	2016	Data-driven	DL	Deep learning fault diagnosis network
56	[87]	2022	Data-driven	DL	Deep learning: spatial–temporal channel prediction
57	[88]	2020	Model-based	NA	Review of traction motor design considerations
58	[89]	2022	Data-driven	NA	Benchmark dataset (MetroPT)
59	[90]	2021	Data-driven	DL	Deep learning: autoencoder-based anomaly detection
60	[91]	2026	Data-driven	Machine Learning	Adaptive Random Forest with explainability
61	[92]	2023	Data-driven	Machine Learning	Random Forest classification approach
62	[93]	2026	Data-driven	DL & ML	Recurrent Neural Network: GRU, LSTM, CNN-GRU-LSTM, and CNN-LSTM

Machine learning algorithms constitute the most frequently adopted family, favored for their comparatively low data requirements and their ability to generalize on the small, unbalanced datasets typical of railway assets:

- Support vector regression (SVR) was used within an online support vector regression architecture to estimate the remaining useful life of train axle bearings from streaming vibration and temperature data [44]; this online formulation updates its regression coefficients incrementally as new samples arrive and relies on a computationally restricted hyperparameter search to remain tractable under continuous data streams.
- K-means clustering was applied to classify motor-current degradation indicators, derived through dynamic time warping, into discrete severity stages for railway door systems [34]; the same unsupervised technique was also used to detect sliding-chair degradation states in point machines from constructed health indicators [42].

- Kernel principal component analysis combined with a weighted Mahalanobis distance was used to extract and fuse multi-sensor features (power curve, vibration, oil level) of a switch machine prior to state classification [36].
- Similarity-based models (hash, pairwise, and residual similarity) and generic supervised machine learning algorithms were reported for RUL estimation and fault comparison across several other studies [41,48,49,54,56,60].

Deep learning approaches are employed where degradation dynamics are strongly nonlinear or sequential, at the cost of requiring larger training sets than classical machine learning:

- A supervised artificial neural network (ANN) was trained on wheel-bearing temperature-time data to predict remaining useful life and detect the onset of degradation in a railcar bearing [35].
- Feed-forward ANN architectures were also reported for reducer and gearbox RUL estimation elsewhere in the corpus [38,52].
- Long short-term memory (LSTM) networks were used to model sequential dependencies in degradation trajectories for RUL prediction [45,47], exploiting their internal memory gates to retain long-range temporal patterns that shallow networks cannot capture.
- Generative adversarial networks (GANs) were applied to reconstruct missing sensor readings prior to RUL estimation for train control and monitoring systems [40], using an adversarial generator-discriminator pair to synthesize missing values consistent with the observed degradation trend.

Model-based approaches relying on stochastic or statistical formalisms remain prevalent where interpretability are required, as in safety-critical infrastructure assets:

- Hidden Markov Model (HMM) was trained on a fused, weighted health indicator to identify discrete degradation states and to compute the expected remaining time of a switch machine before failure [36], with the model's transition probabilities estimated from a labeled training set of prior operating cycles.
- Dynamic Bayesian networks were used to compute prognosis on discrete-state systems by propagating belief updates over successive observations [43].
- A proportional hazards model was applied to relate covariate-driven failure risk to a baseline hazard function for infrastructure component prognosis [51].
- Classical statistical techniques, including spectral and kurtosis analysis of vibration signals, were used to characterize fault signatures [39], reflecting a transition point in the literature between purely statistical degradation description and the AI-based methods that later supplanted it, while a fleet-level statistical prognostics model was also used to schedule opportunistic interventions across a train fleet based on estimated remaining useful life [33].

Hybrid models combine two or more of the above families, most often to compensate for the absence of run-to-failure data on safety-critical railway subsystems:

- A hybrid model-based approach combining a physics-based simulation of an HVAC system with an ensemble of Boosted Trees classifiers was used to detect multiple, potentially co-occurring faults and to estimate the remaining useful life of the air filter from physics-generated run-to-failure data [37].
- The physics-based component supplies synthetic healthy and faulty operating conditions that the data-driven classifier alone could not otherwise learn from.
- A stacking ensemble combining deep neural networks, support vector machines, k-nearest neighbors, and XGBoost, tuned through Bayesian optimization, was used to predict the remaining useful life of a catenary system [32], leveraging the comple-

mentary strengths of its constituent learners to reduce individual model variance. A physics-based prognostics model calibrated with learning algorithms and Monte Carlo simulation was applied to sliding-chair failure prognosis under uncertainty [53].

- A hybrid LSTM-autoencoder architecture was used to jointly compress and forecast degradation signals with reduced sensitivity to noise [59]. Digital twin technologies, integrating a continuously updated physical model with real-time operational data, were used to support advanced analytics for fleet-level maintenance planning [55], and a nonlinear diffusion-based degradation model combined with a Brownian-motion transformation was used to predict the remaining useful life of dynamic multi-component systems [58].
- A mixed-integer linear programming formulation was used to combine data-driven RUL prognostics with the fixed preventive maintenance calendar and depot resource constraints of a real high-speed rail fleet, jointly assigning trains to operation, predictive maintenance, or idle status so as to minimize the loss of component useful life [33], and a comparable prognostics-based scheduling optimization was reported for multi-asset maintenance planning [61].

Figure 8 synthesizes all algorithms identified, divided into 3 categories: data-driven, model-based, and hybrid models.

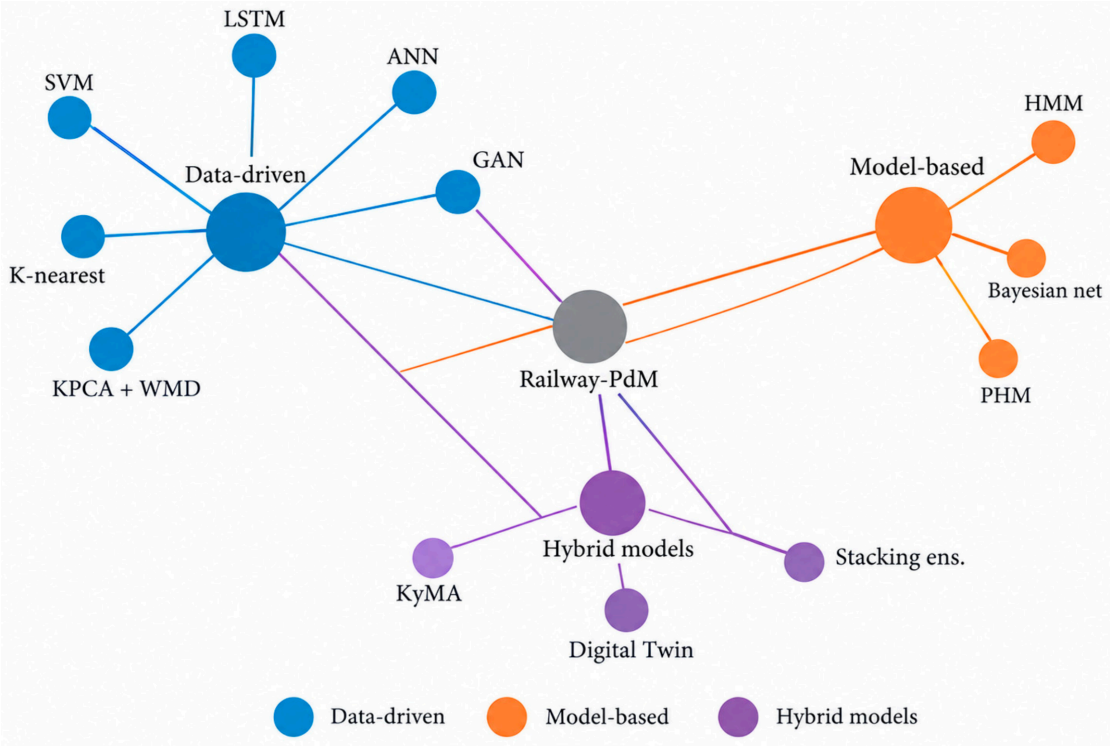


Figure 8. Network map of algorithms used for predictive maintenance in the railway domain.

4.3. Railway Subsystems Addressed

Beyond identifying the algorithms and modeling techniques employed, it is equally important to characterize what these methods have been applied to within the railway system. The reviewed literature consistently targets subsystems that are safety-critical and operationally central to rail transport, components whose failure can compromise passenger safety, disrupt service continuity, or trigger costly unplanned downtime. Wheelsets, current-collection equipment, switch machines, and track infrastructure, in particular, are subject to demanding operating conditions and carry direct implications for both the reliability and the safety of railway operations, which explains why predictive maintenance research

has concentrated so heavily on them: anticipating degradation in these subsystems offers the greatest potential to prevent failures before they occur, extend component service life, and support safer, more dependable rail operations.

Wheelset-related components, wheel bearings, axle bearings, and the wheel-rail contact interface, remain the most extensively studied asset family, now accounting for twelve of the corpus's asset-specific contributions [13,18,27,35,38,39,44,68–72]. Recent additions reinforce this concentration with wayside and onboard condition-monitoring reviews [68], deep-learning models for out-of-round wheel detection [69], transformer-based wheel-wear prediction [70], residual-learning CNN architectures for wheelset bearing diagnosis [71], and continual-learning approaches addressing the non-stationary nature of in-service wheel-track monitoring data [72]. This concentration remains consistent with the engineering rationale identified previously: wheelset degradation is a leading contributor to unplanned withdrawals from service, and the relevant failure mechanisms generate well-characterized vibration and thermal signatures that are comparatively straightforward to instrument.

The current-collection subsystem catenary, pantograph, and the pantograph carbon contact strip (PCCS) doubles in representation to eight studies [14,25,32,48,73–76], with newly identified work spanning fuzzy-classifier predictive maintenance for the pantograph–catenary interface [73], deep-learning-based arc detection [74], image-processing-based fault diagnosis [75], and Wiener-process degradation modeling of the PCCS itself [76].

Switch and point machines show the largest gain, rising to twelve studies [36,42,56,57,77–84], reflecting an intense recent research effort in this asset family: deep reinforcement learning [77], improved deep convolutional network and support vector data description classification [78], multi-sensor fusion tensor machines [79], expert-system and Bayesian-network diagnosis [80], deep random forest fusion [81], diagnosis frameworks for high-performance switch systems [82], acoustic degradation recognition [83], and a dedicated review of point-machine fault detection challenges [84]. HVAC systems remain at four studies [26,37,52,53], and gearboxes and mechanical transmission components remain at two [22,54], indicating that these asset families, while adequately represented, have not seen the same recent research intensity as wheelsets, current collection, or switch machines.

Fleet-level and rolling-stock-wide asset management grows to six studies [21,33,47,51,85,86] with the addition of streaming data-driven maintenance frameworks [85] and real-time online-learning pipelines for predictive maintenance [86]. Track and network-level infrastructure similarly grows to eight studies [16,19,20,55,64–67], reinforced by a dedicated review of machine-learning methods for track geometry degradation prediction [64], artificial-neural-network case studies of track degradation [65], a review of vehicle-based track condition monitoring [66], and a bibliometric systematic review of rail transport condition monitoring [67]. Though, as noted previously, this growth remains concentrated in scheduling- and degradation-modeling approaches rather than direct condition-based sensing of the track structure itself.

Train control and monitoring systems (TCMS), radio communication and signaling equipment, and traction and propulsion systems each gain one additional study, respectively: a deep-learning fault diagnosis network for onboard equipment [87], a deep-learning channel-prediction framework for railway communication networks [88], and a review of traction motor design considerations for railway applications [89], bringing each of these categories to two studies apiece [23,24,40,87–89].

Brake and pneumatic supply system represented by four studies [90–93], all built around the publicly available MetroPT benchmark dataset collected from the air production unit of a Porto metro train [90]. This includes the original anomaly detection framework using deep learning [91], a subsequent explainable machine-learning pipeline achieving

above 98% F-measure on the same asset [92], and a classification-based approach to air-production-unit failure diagnosis [93]. The emergence of this category illustrates a broader pattern in the field: the availability of an open, well-documented benchmark dataset can rapidly concentrate research attention on a previously unstudied subsystem, in much the same way that accessible vibration and thermal datasets appear to have driven the wheelset literature's dominance.

Consequently, predictive maintenance research in the railway domain remains concentrated on rolling-stock components that are both individually critical and comparatively easy to instrument; wheelsets and switch machines alone now account for nearly 40% of all asset-specific studies reviewed, while door systems, and to a lesser extent traction, TCMS, and signaling equipment, remain markedly underrepresented. The emergence of the brake and pneumatic supply category as an artifact of open benchmark data availability, rather than of any change in the underlying safety or economic importance of that subsystem, reinforces the conclusion that current research priorities in railway predictive maintenance are shaped as much by data accessibility as by asset criticality. Figure 9 summarize all sub-systems identified in the collected studies.

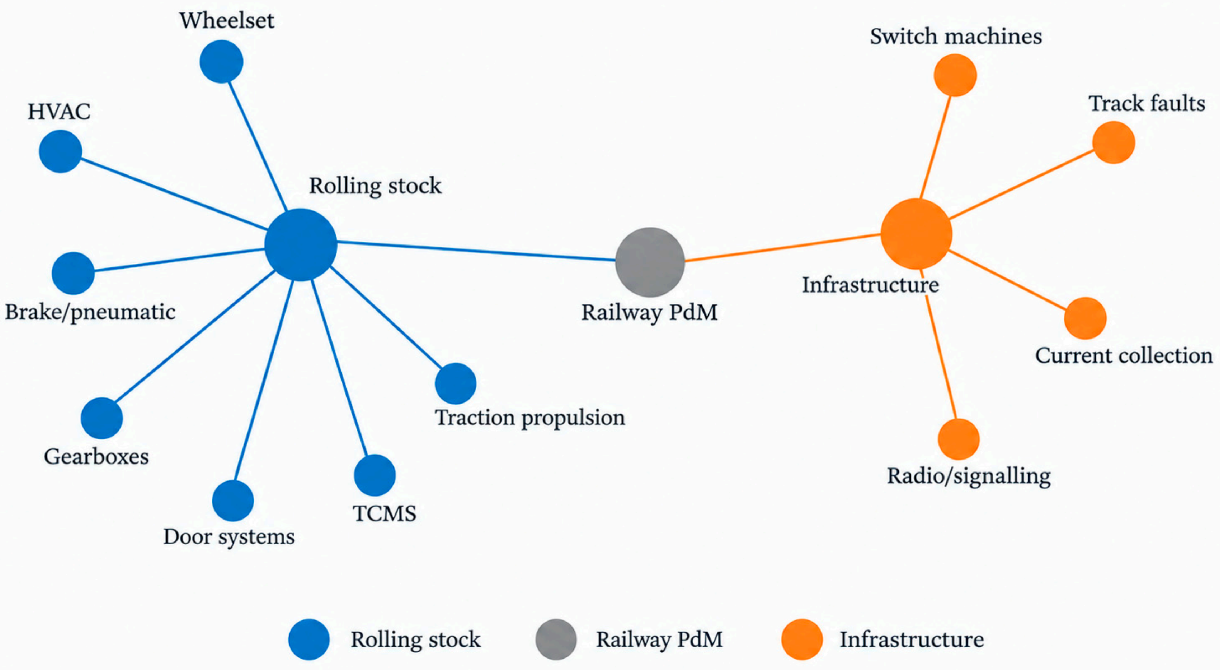


Figure 9. Distribution of railway subsystems addressed, by asset category.

5. A Hybrid Predictive Maintenance Framework

5.1. Predictive Maintenance Flowchart

This section presents a proposed hybrid framework Figure 10, comprising a set of essential steps applicable regardless of the specific problem addressed. The process begins with the real-time acquisition of data through embedded sensors and IoT devices, which is stored in cloud infrastructure or dedicated servers. The subsequent phase consists of preprocessing the acquired data, including filling data gaps, removing duplicates, and filtering out noisy signals. The third step involves selecting the most informative indicators and retaining only the features relevant to monitoring machine health. The predictive model is then trained using historical maintenance and failure data, after which it uses the cleaned data to compute the remaining useful life (RUL).

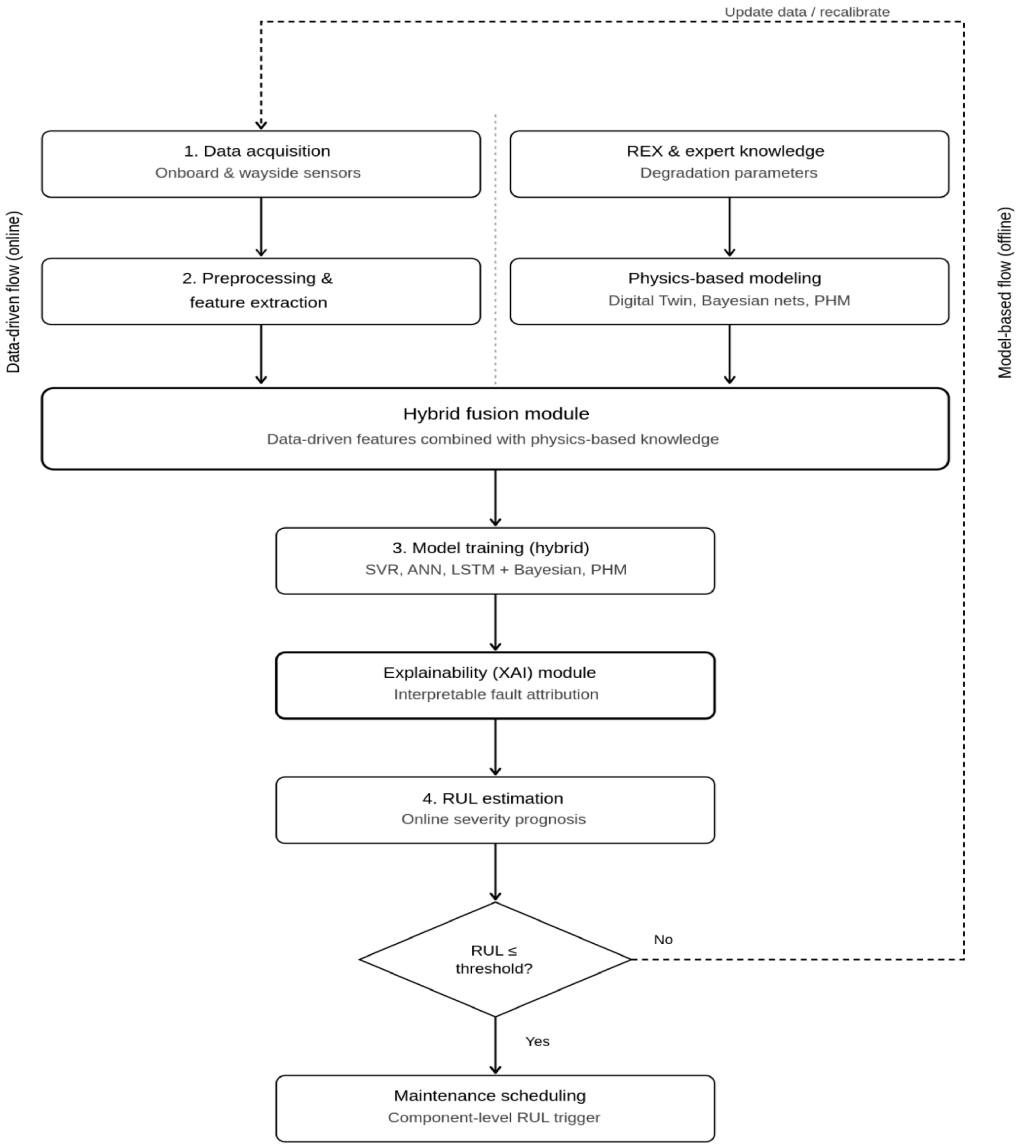


Figure 10. Proposed hybrid predictive maintenance framework for the railway domain.

5.2. Framework Phases

5.2.1. Data Acquisition and Storage

Data acquisition constitutes the foundational phase of predictive maintenance. In the rail domain, data are collected from multiple sources, including onboard sensors (e.g., temperature, force, and current sensors) and wayside detectors such as signaling equipment and GSM radio communication systems. These data capture both the operational conditions and the health state of various assets. The acquisition process must ensure high data quality and accuracy in real time, irrespective of environmental conditions.

5.2.2. Preprocessing & Feature Extraction

Raw railway data are often affected by noise, missing values, outliers, sensor drift, and communication errors. Data cleaning aims to improve data quality and consistency prior to analysis. This phase typically involves signal filtering [45], removal of erroneous or irrelevant measurements, handling of missing data through interpolation or imputation techniques, and normalization to ensure comparability across operating regimes. In the railway context, data cleaning is particularly critical given the variable operating conditions, such as speed changes, load variations, weather effects, and track geometry, all of which

may introduce non-informative variability into the data. Feature extraction transforms the cleaned data into representative indicators that capture the degradation behavior of railway components. These features may be derived in the time domain, the frequency domain, or the time–frequency domain, with effective feature extraction aiming to enhance sensitivity to early fault signatures while reducing data dimensionality. In railway predictive maintenance, features are often designed to reflect specific physical degradation mechanisms, such as bearing wear, wheel flats, insulation aging, or track deterioration, thereby improving the interpretability and robustness of the resulting predictive models.

5.2.3. REX, Expert Knowledge, and Physics-Based Modeling

In parallel to the online, data-driven flow, an offline model-based flow provides complementary degradation knowledge that historical data alone cannot provide. Return of experience (REX) and expert engineering judgment characterize known failure modes and degradation mechanisms for each subsystem, informed by prior maintenance records. This knowledge is formalized through physics-based and stochastic models, including digital twin simulations [55], Bayesian networks [43], and the proportional hazard model [51], which represent degradation behavior even where historical run-to-failure data remain scarce.

5.2.4. Hybrid Fusion

The condition indicators derived from the online data-driven flow and the degradation knowledge derived from the offline model-based flow are combined in a hybrid fusion stage. This fusion compensates for the principal limitation of each individual approach: data-driven methods require substantial historical datasets rarely available for safety-critical railway components, while model-based methods require accurate physical parameters that are difficult to calibrate without empirical data. Fusion strategies identified in the reviewed literature include feature-level combination and the use of physics-based models to generate synthetic training data that augment sparse real-world datasets [37].

5.2.5. Model Training

The fused representation is used to train a hybrid model that learns the relationship between the extracted features, the degradation knowledge supplied offline, and the health state of railway assets. Depending on data availability and labeling, supervised, semi-supervised, or unsupervised learning approaches may be employed, as identified in Section 4.2. The training process involves parameter optimization, validation, and performance evaluation to ensure generalization across different operational conditions and asset populations.

5.2.6. Explainability

Given the safety-critical nature of railway operations, model outputs are further accompanied by an explainability module that attributes predictions to specific input features or condition indicators. This interpretability requirement is essential for maintenance decisions to be auditable and accepted within a safety-regulated operating environment [92].

5.2.7. Remaining Useful Life Estimation

Remaining Useful Life (RUL) estimation represents the ultimate objective of predictive maintenance. This phase focuses on predicting the time or number of usage cycles remaining before a component reaches a predefined failure threshold or an unacceptable performance level, combining the hybrid model's output with real-time condition monitoring to generate prognostic insights. In the railway domain, accurate RUL predictions enable optimized maintenance scheduling, reduced downtime, improved asset availabil-

ity, and enhanced safety. Two outcomes are possible: if the RUL reaches the predefined threshold, a maintenance action is scheduled; otherwise, the data are updated as new measurements become available and the cycle is repeated. This process is iterative, with the RUL estimate refined at each iteration. The proposed framework is thus designed to support maintenance decision-making, reduce downtime and cost, and improve overall reliability and availability.

6. Discussion

In answer to RQ1 (algorithmic approaches and their evolution), the analysis presented in Section 4.2 shows that railway predictive maintenance research is now overwhelmingly data-driven: of the 61 studies analyzed, 80.3% employ purely data-driven methods, 16.4% adopt hybrid architectures combining physics-informed simulation with data-driven learning, and only 3.3% rely on purely model-based formulations. Within this landscape, methodological choice appears to track data availability more closely than algorithmic preference alone: hybrid architectures, unsupervised clustering, and synthetic data generation recur specifically where labeled failure data are scarce (door systems, HVAC filters, switch machines), whereas supervised regression and deep learning dominate where instrumentation is mature and historical failure records are abundant (wheelsets, current collection). This pattern suggests that the field's methodological evolution has been shaped as much by the practical constraint of run-to-failure data scarcity on safety-critical assets as by advances in algorithms.

In answer to RQ2 (subsystem coverage and underexplored assets), the analysis in Section 4.3 shows that wheelsets and switch machines together account for approximately 40% of the asset-specific studies reviewed, a concentration that tracks data accessibility at least as closely as asset criticality, illustrated most clearly by the rapid emergence of the brake/pneumatic supply category following the public release of the MetroPT benchmark dataset. Over the past five years specifically, three developments stand out: (i) an acceleration of deep learning and hybrid modeling applied to switch machines and current-collection assets, including deep reinforcement learning, tensor-fusion diagnosis, and transformer-based wear prediction; (ii) increasing attention to explainability and online/continual learning, reflecting the operational requirement for maintenance decisions that are both real-time and auditable within safety-regulated environments; and (iii) an expansion of track-level degradation modeling, although this remains concentrated on scheduling and reliability optimization rather than direct condition-based sensing of the physical infrastructure. By contrast, door systems, traction and propulsion, onboard communication, and train control and monitoring systems (TCMS) remain markedly underrepresented. A disparity that is difficult to justify on safety or operational grounds alone, and one that more plausibly reflects the practical difficulty and cost of instrumenting these subsystems relative to the rotating and sliding-contact components that dominate the reviewed corpus.

In answer to RQ3 (comparative strengths and limitations of the methodological families), the trade-offs identified in Section 4.2 are consistent with, and help explain, the distribution reported above: data-driven methods offer scalability and lower deployment cost but depend on data quality and volume that many railway subsystems cannot yet provide; model-based approaches offer interpretability at the cost of the domain expertise and calibration effort required to build them; and hybrid approaches partially reconcile this trade-off, at the cost of the additional integration complexity, which likely explains why they remain a minority approach (16.4%) despite their apparent suitability for exactly the data-scarce subsystems discussed above.

In answer to RQ4 (barriers to fleet-level deployment), the literature reviewed here remains concentrated at the level of individual-component prognostics; only a small subset of the studies examined, most notably the fleet-scheduling optimization work discussed, extend a component-level RUL estimate into an operational, resource-constrained maintenance decision. This indicates that the translation from predictive algorithms to deployable fleet-level maintenance planning remains one of the least developed aspects of the field, independent of the methodological family employed.

In answer to RQ5, these findings collectively motivate the hybrid framework proposed in Section 5. Figure 10, which is offered here as a conceptual synthesis of the approaches and gaps identified through this review, rather than as an empirically validated solution; its principal contribution is to make explicit the online/offline structure of condition monitoring paired with degradation modeling that recurs implicitly across the hybrid studies surveyed, and to flag the component-to-fleet integration gap identified above as a priority for future work.

7. Conclusion and Future Work

This review has synthesized the algorithms, techniques, and subsystem applications that define the current state of predictive maintenance research in the railway domain, guided by a PRISMA method with defined inclusion and exclusion criteria. The evidence indicates a clear trend toward data-driven methods, which now dominate the reviewed corpus with various ML and DL algorithms. However, the lack of high-quality real-world data remains a major challenge for the implementation of predictive maintenance solutions. Digital twins offer a promising approach to address this challenge by supporting data generation, simulation, and model development. Furthermore, future research should investigate how predictive maintenance outputs, particularly fault probabilities and RUL estimation, can be translated into maintenance decisions. For example, an estimated RUL can be compared with predefined decision thresholds to determine whether an asset should be kept in operation, repaired, or replaced, and to identify the most appropriate timing for the intervention. These actions could improve asset reliability and reduce maintenance costs and service downtime.

Although predictive maintenance has been extensively studied in recent years, its application within the railway domain remains relatively underexplored. Given the substantial costs associated with maintenance activities, continued research in this field is essential. Building on these findings, four directions are suggested:

- First, future work should extend hybrid physics-informed modeling, shown here to be effective precisely where labeled failure data are scarce, to these same underrepresented assets.
- Second, deliberate efforts to generate or release open benchmark datasets for underrepresented and critical subsystems (door systems, TCMS, traction motors) would likely accelerate research, in the same way that the availability of open datasets has already driven progress for other subsystems.
- Third, greater emphasis is needed on explainable and online-learning architectures that can operate under real-time constraints of safety-regulated railway operations, rather than offline models validated solely on static datasets.
- Finally, predictive maintenance should evolve beyond RUL estimation toward prescriptive maintenance frameworks that support effective maintenance decision-making and action recommendation.

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