Proceedings of the 5th Indian International Conference on Industrial Engineering and Operations Management, Vellore, Tamil Nadu, India, November 6-8, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/IN05.20250188
Published: November 6, 2025

A Literature Review of Predictive Maintenance in Rail Transport, Current Trends and a Novel Framework

Driss El Hor
PhD Student
Engineering Sciences Laboratory
National School of Applied Sciences
Ibn Tofail University, Kenitra, Morocco
driss.elhor@uit.ac.ma

Rachid Bannari
Full Professor
Engineering Sciences Laboratory
National School of Applied Sciences
Ibn Tofail University, Kenitra, Morocco
rachid.bannari@uit.ac.ma

Abstract

In the contemporary academic and industrial contexts, predictive maintenance has emerged as a pivotal concern, particularly in the era of artificial intelligence's integration into maintenance operations. This technique promises notable benefits, including cost savings, increased component remaining useful life, enhanced system availability, and the capability to monitor operations in real time. There are three primary categories of predictive maintenance: the data-driven approach, the model-based method and the hybrid model. In railway maintenance play a pivotal role to avoid line interruption and ensure high rolling stock availability. This article provides a comprehensive review underscoring the main methods utilized in recent years thorough a deep analysis of 599 relevant articles obtained from scientific databases. PRISMA method was used to scan relevant studies in the last two decades in three popular databases: Scopus, Web of science and Science Direct. Accordingly, the study presents a survey of predictive maintenance frameworks, approaches and algorithms, in which data driven approach using machine and deep learning techniques were widely employed. Also, it shed light on the major rail equipment that was the focus of the researches. To harness the complementary strengths of both data-driven and model-based, we have proposed a novel hybrid framework that synergistically integrates real-time analytics with theoretical modeling. In conclusion, limitations and challenges were introduced with potential improvements and perspectives for future work.

Keywords
Predictive maintenance, Remaining useful life, Railway Industry, Artificial Intelligence, Machine Learning

1. Introduction
Maintenance is an issue that has for a long standing the utmost importance in multiples industries (Coandă et al., 2020). In particular for leading manufacturers and industries with critical systems such as aeronautics, space, railway and automotive. The timely selection of the most appropriate maintenance approach can lead to a significant reduction in operational costs (Shey-Huei et al., 2015), minimize disruption (Mitici et al., 2023) as well as increase assets remaining useful life. There are various types of maintenance that have been discussed in the literature. However, the

most well-known categories for both academia and industry are preventive and corrective maintenance (Wang et al., 2016).

Predictive Maintenance is one of the major strategies of interest in the fourth industrial revolution, it is a technique that can predict failure and detect faulty machine state thought estimating the remaining useful life. As highlighted in previous works (Li et al., 2022), several forms have been identified, when the authors have differentiated five techniques in real world application: experience-based, model-based, physical-based, data-driven, and hybrid model. Nonetheless, in the literature three main forms are frequently described, model-based method that include the experience physical modeling. A data-driven method involves building the model using operational data including historical failure records and condition monitoring, often incorporating large volumes of real-time data, and finally the hybrid model. Additionally, Wu et al. (2024) described Remaining Useful Life (RUL) as a key parameter in health management and equipment monitoring; it is defined as the useful life left in equipment at a specific point in its lifecycle (Li & He, 2015). And so, it remains essential for preventing failures and build a Predictive Maintenance frameworks (Hadi et al., 2024).

In the rail industry, maintenance is a key factor for operational availability and safety, and an important cost life-cycle-costing contributor and impactor (Dersin, 2020). According to Reliability, Availability, Maintainability and Safety (RAMS) management, maintenance plays a crucial role in achieving the safety of rail infrastructure and avoiding catastrophic incidents (Kavitha et al., 2025). Data driven approach with the use of AI is transforming railway systems by enabling smarter and early detection of faults and optimizing maintenance schedules. Kalapati et al. (2024) developed an AI-based approach that uses classification and anomaly detection to enhance the reliability of railway radio communication systems. Likewise, (Soy and Vij, 2025) demonstrated how AI can optimize predictive maintenance of hybrid and electric rail systems by predicting faults in real time and adapting maintenance plans accordingly.

Although predictive maintenance has been extensively studied in the literature, their implementation in real-world operations remains limited for rolling stock. Therefore, this paper aims to review the recent methods developed in the context of Predictive Maintenance, especially for railway areas. This investigation is structured as follows: the next section defines the general methodology and related works, section 3 presents the results obtained with a detailed analysis of technique, algorithms and issues pinpointed. In section 4 we have introduced a comparative analysis. Section 5 is developed to present a novel hybrid framework. Finaly, the conclusion is presented in section 6.

2. Method

The state of art was conducted based on the combination of Systematic Mapping Studies (SMS) (Petersen et al., 2008) and systematic literature review SLR (Petersen et al., 2015) in the process identified as follow: definition of research questions, search for relevant articles, screening of papers with the application of inclusion and exclusion criteria, papers analyze and data extraction. These represent the key phases of the PRISMA method. In this work we aim to shed light about Predictive Maintenance, its recent methods and approaches for a real-world application in railway domain. the following research questions are addressed:

- What are the recent approaches / techniques identified?
- Which issues / components were addressed?
- What are the PdM frameworks pinpointed?
- What are the PdM challenges and perspective?
- What are the possible improvements and contributions?

The research of relevant papers was conducted by selecting the scientific databases. The most popular electronic sources in scientific research and engineering applications are Scopus, Science Direct and Web of Science, in which another digital library is included. All electronic databases provide several search options. Table 1 below outlines the search strategy applied to each database. To identify relevant publications, searches were conducted within the article title, abstracts, and keywords for Scopus and ScienceDirect, while for Web of Science, the search was carried out across all fields.

Table 1. Search strategy used across scientific databases

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

This step consists of the definition of the search string, in order to scan databases and cover all potentially relevant studies and information that could enable us to answer the global problematic addressing by this paper. For this, the keywords are defined and the Boolean operators such as "AND", "OR" are used to construct a combination, that limit as much as possible the number of papers. In the first automatic search we utilized the following keywords "predictive maintenance" combined with "Railway" and its synonym as "rail industry" and "rolling stock". Then we have added "Remaining Useful Life" as a key metric for PHM. Table 2 defines the 2 search queries created to extract the desired insights according to the research questions.

Table 2. Search query algorithms

N°	Search string
1st search	(("Predictive maintenance") AND ("Railway" OR "rolling stock" OR "rail industry))
2nd search	(("Predictive maintenance") AND ("remaining Useful Life") AND ("Railway" OR "rolling stock" OR "rail industry"))

3. Results and Discussion

4.1. Numerical and graphical Results

Figure 1 shows the results obtained in the first and second automatic searches using the queries mentioned above, according to available search. In fact, the research in predictive maintenance applications for railway sector remains low compared to other areas such as manufacturing, aeronautic or automotive. In Scopus over 13 000 papers were obtained when we have used just "predictive maintenance" without "railway" and its synonyms in the search string. As shown a total of 599 documents were found, in which more than 50% are recovered from Scopus. In the first search using the following query ("Predictive maintenance") AND ("Railway" OR "rolling stock" OR "rail industry") 342 were collected from Scopus, 47 from Web of science and 210 found in Science Direct. When employed the second query ("Predictive maintenance") AND ("remaining Useful Life") AND ("Railway" OR "rolling stock" OR "rail industry") the numbers of papers are clearly reduced to 50 papers in Scopus, 14 in Web of Science and 6 in SD, due to the elimination of papers that does not introduce the notion of the Remaining Useful Life in their studies.

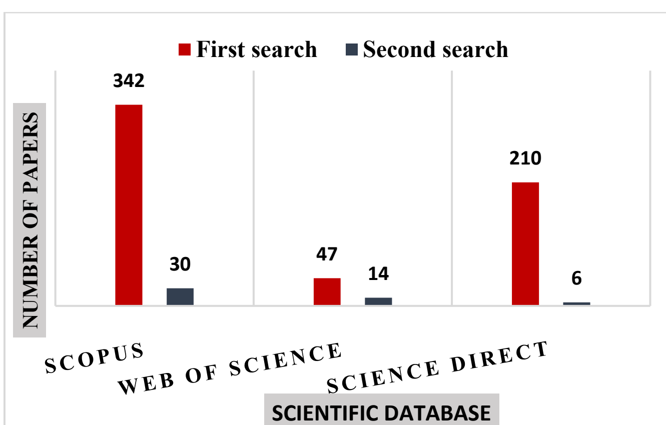

Figure 1. Number of papers obtained within databases

Using the second automatic search with the following string ("Predictive maintenance") AND ("remaining Useful Life") AND ("Railway" OR "rolling stock" OR "rail industry") 50 papers were obtained. Also, PRISMA Method was used, firstly duplication studies between databases were removed. Then, to narrow down the result, inclusion and exclusion criteria are applied, we have considered those published as article or conference, between 200 and 2024, writing in English and finally published in open access to helps us in analyzing phase. Although 31 articles met the inclusion and exclusion criteria and only 13 articles that were both open access and available for peer review were retained in the final selection, in which the authors have addressed mainly the PdM and RUL estimation in railway domain.

The research in this area has begun over the past decade as shown in Figure 2 that illustrates the yearly evolution of publications on predictive maintenance from 2004 to 2024. The figure is obtained from Scopus on August 17, 2024. As shown between 2004 and 2015 the number of papers remained low and relatively stable which varies between 0 and 10 per year, indicating limited research activity in this fields during that period. A significant increase is observed after 2016, with a sharp rise in 2021. This evolution was conducted by the advancements of data-driven technologies, including deep learning and machine learning algorithms. Allowing to detect anomalies and predict failures before they occur. The IoT devices as smart sensors have enabled real-time monitoring of critical railway components. In addition, the peak in 2023 reflects heightened academic and industrial interest, while the drop in 2024 may be due to publication delays notably for reviewing articles in one of the most critical sectors as rolling stock.

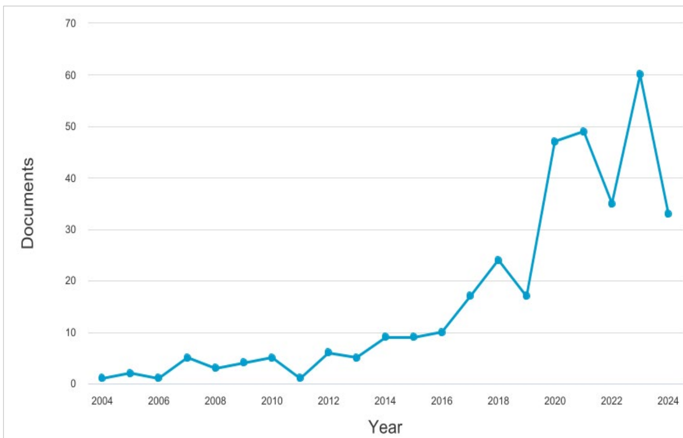

Figure 2. Evolution of the documents by publication year

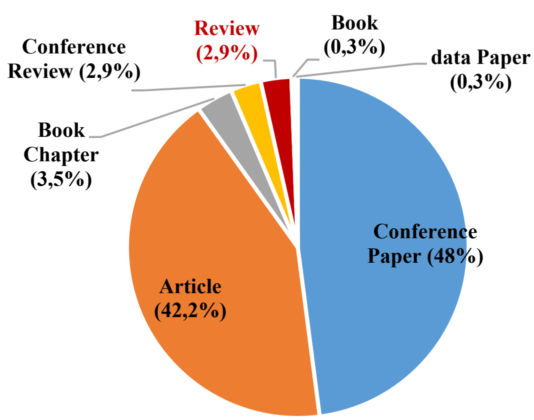

Figure 3. Distribution of documents by paper type

Figure 3 presents the distribution of papers categorized by publication type in Scopus electronic database. The majority of the documents are conference papers (48%) and journal articles (42.2%). In contrast, Book chapters (3.5%) and review papers (2.9%) are less represented, reflecting limited efforts in summarizing existing knowledge. Then minor categories such as books (0.3%), data papers (0.3%), and conference reviews further highlight the field's current focus on original research rather than secondary literature or reference materials. Overall, the figure illustrates a significant lack of review article that summarize and synthesis the research trends. for instance, in Scopus among 342 filtered in the first automatic search, only 10 studies were published as a review article corresponding of less than 3% of total documents.

The emergence of Industry 4.0, Artificial intelligence AI and Internet of Things IoT had a significant contribution in the developed methodologies over the past decade. Figure 4 shows that the Data-driven method was widely harnessed by authors in collected articles, over 75% have integrated this technique, 7% have deployed physical modeling and 18% have suggested a hybrid model that combines data driven and model-based to build a predictive mechanism. Furthermore, the authors have employed various methods according to paper case study and the available resources. Related to the reviewing articles 2 sub-types were distinguished for data-driven approach, the first is Machine Learning and deep learning methods, the second is the stochastic methods. Moreover, they are enormous algorithms implemented in predictive maintenance applications as ANN, SVM and K Means clustering.

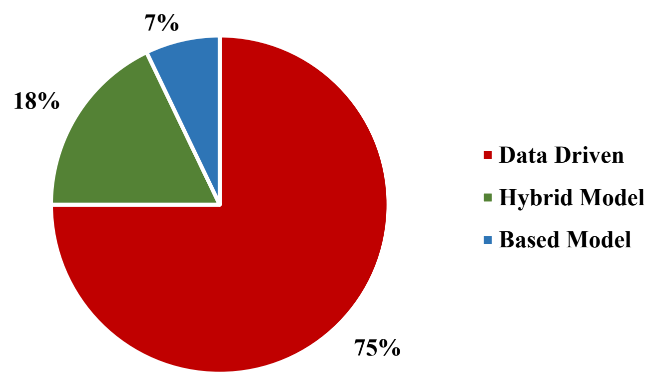

Figure 4. Classification of Predictive maintenance approaches by 31 papers

Table 3 and Table 4 below provide a summary of the data gathered from each study. featuring a classification of the articles based on their year of publication

Table 3. Approach and algorithms

N°	Reference	Year	Approach	Algorithm
1	(Liu et al., 2023)	2023	hybrid model	ML, Stochastic modeling Bayesian optimization
2	(Crespo del Castillo et al., 2023)	2023	Data-driven	Statistical modeling
3	(Shimizu et al., 2023)	2023	Data-driven	ML, unsupervised learning K-means clustering
4	(Daniyan et al., 2022)	2022	Data-driven	ML, supervised learning Artificial Neural Network
5	(Zheng et al., 2022)	2022	Data-driven	ML, Stochastic modeling Hidden Markov Model
6	(Gálvez et al., 2021)	2021	hybrid model	ML, supervised learning Support Vector Machines
7	(Daniyan et al., 2020)	2020	Data-driven	ML, supervised learning Artificial Neural Network
8	(Daniyan et al., 2020)	2020	Data-driven	Statistical modeling spectrum and kurtosis analysis
9	(Lee et al., 2020)	2020	Data-driven	ML, Generative Adversarial Network
10	(Li et al., 2020)	2020	Data-driven	Models' comparison
11	(Atamuradov et al., 2018)	2018	hybrid model	ML, unsupervised learning k- means Clustering
12	(Foulliaron et al., 2017)	2017	Data-driven	Stochastic modeling dynamic Bayesian networks
13	(Fumeo et al., 2015)	2015	Data-driven	ML, supervised learning Support Vector Regression SVR

Table 4. methodologies pinpointed and the component studies

N°	Reference	Paper title	Component	Methodology
1	(Liu et al., 2023)	Remaining Useful Life Prediction for a Catenary, Utilizing Bayesian Optimization of Stacking	Catenary	Stacking ensembles algorithms (DNN, SVM, KNN, XGBoost) to design a unique leaner
2	(Crespo del Castillo et al., 2023)	Dynamic fleet maintenance management model applied to rolling stock	Train fleet	Predictive maintenance optimization based on the REX of maintenance and operations scheduling
3	(Shimizu et al., 2023)	RealTime Prognostics and Health Management Without Run to Failure Data on Railway Assets	door systems	Asset prognostic based on fault severity assessment based on dynamic time warping method and K means algorithm
4	(Daniyan et al., 2022)	Implementation of Artificial intelligence for maintenance operation in the rail industry	wheel-bearing	5 phases: data acquisition, pre-processing, network training, features extraction and predictive model.
5	(Zheng et al., 2022)	Prediction of the Remaining Useful Life of a Switch Machine, Based on Multisource Data	Switch Machine	health indicator construction based on the weighted Markov distance. HMM were used for RUL prediction
6	(Gálvez et al., 2021)	Fault detection and RUL estimation for railway HVAC systems using a hybrid model-based approach	HVAC	The proposed HyMA combines physics-based models with data-driven models.
7	(Daniyan et al., 2020)	Artificial intelligence for predictive maintenance in the railcar learning factories	wheel-bearing	5 phases: data acquisition, pre-processing, network training, features extraction and predictive model.
8	(Daniyan et al., 2020)	Development of a diagnostic and prognostic tool for predictive maintenance in the railcar industry	wheel-bearing	5 phases: data acquisition, pre-processing, network training, features extraction and predictive model.
9	(Lee et al., 2020)	Generative adversarial network based missing data handling and remaining useful life estimation for smart train control and monitoring systems	TCMS	RUL estimation framework applied in the context of big data, in which GAN were deployed
10	(Li et al., 2020)	Comparison of data driven prognostics models: A process perspective	all	Comparison of methodologies
11	(Atamuradov et al., 2018)	Degradation level Assessment and Online Prognostics for Sliding Chair Failure on Point Machines	Point Machines	Construction of HI and the degradation model. Then, in online phase K-means was used for system's health states variation
12	(Foulliaron et al., 2017)	A dynamic Bayesian network approach for prognosis computations on discrete state systems	NA	Bayesian network optimization was employed to predict the RUL
13	(Fumeo et al., 2015)	Condition based maintenance in railway transportation systems based on big data streaming analysis	Axle-bearings	Collect and analyze the data come from different sensors, which Support Vector Regression was utilized to predict the RUL

4. Methods comparison

Table 5. Method comparison

Approach	Advantages	Limitations	Studies that address these limitations
Data Driven	Big data analysis Automatic treatment Low cost	Lack of data	(Shimizu et al., 2023)
		Data quality	(Davari et al., 2021)
		Low accuracy	(Atamuradov et al., 2018)
		IoT and AI integration	(Daniyan et al., 2022)
Model based	Good system definition High precision	System complexity High cost	(Atamuradov et al., 2018)
Hybrid model	Robust system understanding High accuracy Variable cost	Integration	(García-Méndez et al., 2025)
		Lack of data	(Shimizu et al., 2023)

In evaluating the comparative analysis of data-driven (Table 5), model-based, and hybrid approaches, it becomes evident that each method offers distinct advantages and inherent limitations. Data-driven methods excel in scalability and cost-efficiency. However, their efficacy is related to the availability and quality of significant datasets, often constrained by IoT integration challenges. Conversely, model-based approaches provide high precision and well-defined system representation. Yet, they are hampered by elevated costs and the difficulty of modeling unknown degradation mechanisms. Hybrid models attempt to reconcile these extremes by integrating empirical data with theoretical constructs, yielding robust system understanding and enhanced accuracy. Nonetheless, their implementation demands expert knowledge, return of experience (REX), and sufficient data, which may not always be accessible. The integration complexity further complicates their deployment in dynamic environments. Overall, the choice of approach must be context-sensitive, balancing precision, adaptability, and resource constraints.

To harness the complementary strengths of both data-driven and model-based, we have proposed in next section a novel hybrid framework that synergistically integrates real-time analytics with theoretical modeling, thereby enhancing system adaptability, precision, and resilience across diverse operational contexts. Therefore, it is fully compatible with all critical train components

5. Proposed framework

This section provides a proposed hybrid framework with an essential step regardless of problematic treated. The process starts with an acquisition of data in real-time by using several embedded sensors and IoT devices. Cloud or special servers are used to store these big data. Next phase consists of pre-processing acquired data to complete the gap, delete duplication or eliminate noisy signals; filters are required. The third step consists of selecting the best indicators and work only with the important features that allow the monitoring of the machine health. The predictive model was trained using historical maintenance and past failure data, then it uses the cleaned data to calculate the remaining useful life RUL. The latest is evaluated in comparison to its end-of-life threshold, if it is found to be approaching this limit, predictive maintenance is recommended to mitigate potential failures. Otherwise, the evaluation process is reiterated using updated data inputs to refine the predicting process.

Several studies have introduced hybrid models for predictive maintenance, which offer significant advantages but enormous limitations. Their integration complexity demands robust synchronization between heterogeneous data sources and degradation models. The effectiveness of data-driven phase is highly dependent on the quality and availability of data (Davari et al., 2021), which may be compromised in real-world railway environments.

Additionally, accuracy remains a challenge, particularly when DL techniques are involved, limiting transparency in decision-making (Atamuradov et al., 2018). Our proposed framework presents simplified design for rail predictive maintenance, combining continuous monitoring in On-line stage and a dynamic degradation modeling in Off-line stage. The process is continuously enriched through iterative updates, which contribute to its sustained accuracy and operational robustness. The Figure 5 illustrate this method step by step.

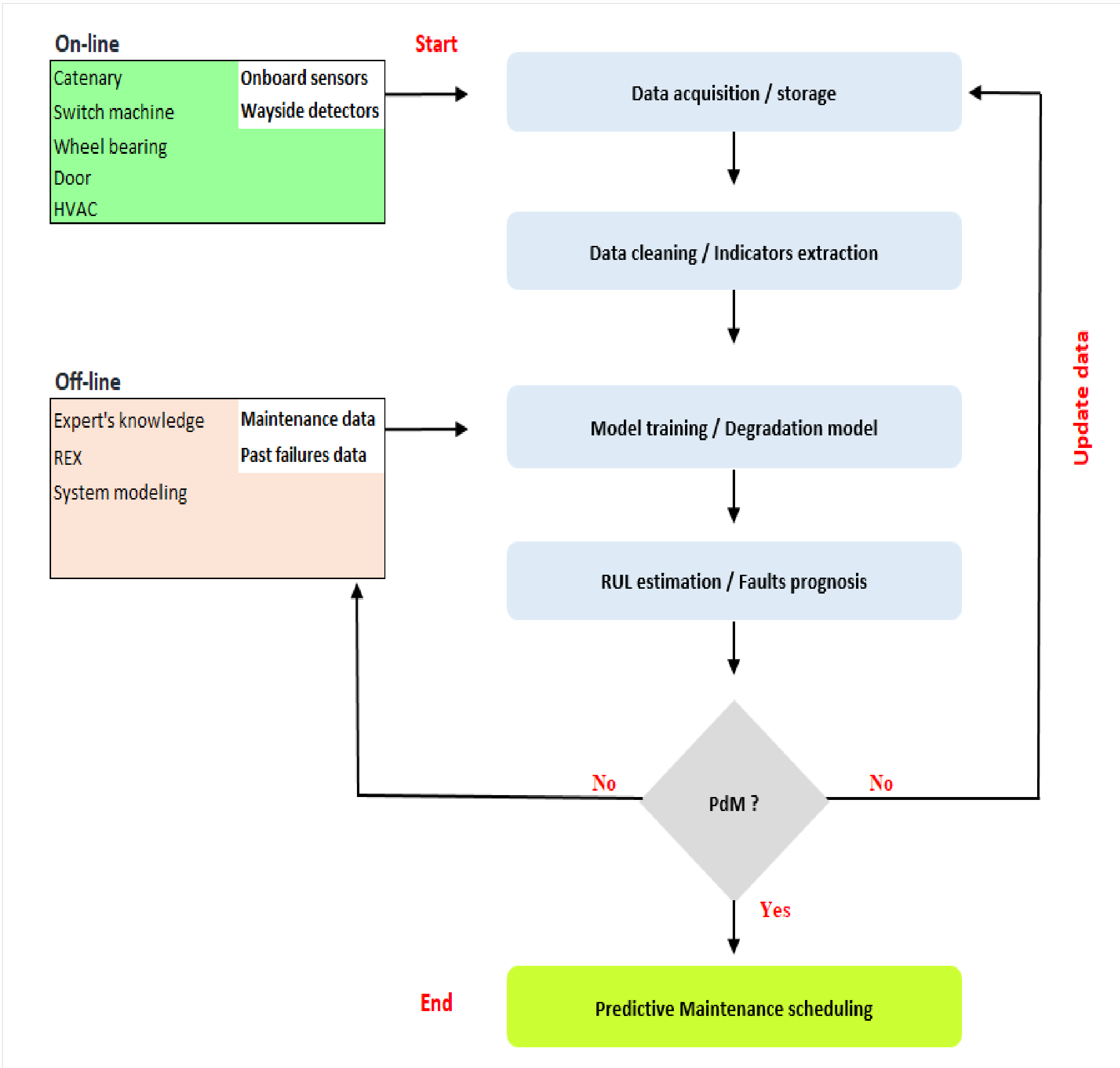

Figure 5. Proposed predictive maintenance framework

6. Conclusion

This study provides a novel hybrid framework and comprehensive review of predictive maintenance within the railway sector. To achieve this, a systematic literature review methodology was employed, utilizing the PRISMA framework to extract relevant publications. Subsequently, the approaches and algorithms adopted across the selected studies were identified, followed by various statistical analyses. The results indicate that the vast majority of the reviewed papers have adopted data-driven techniques, while only a limited number proposed model-based or hybrid approaches. Furthermore, the most frequently studied railway components were identified, along with an overview of the methodologies implemented. The analysis highlights a significant need for effective and economic predictive maintenance solutions. For this raison we have proposed a novel hybrid framework that synergistically combines real-time analytics with theoretical modeling, beginning with data acquisition and preprocessing, and concluding with model training aimed at estimating the Remaining Useful Life (RUL).

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. Future work will focus on integrating deep learning-based predictive maintenance strategies to support more effective decision-making.

References

Atamuradov, V. and Medjaher, K., Degradation-level assessment and online prognostics for sliding chair failure on point machines, IFAC-PapersOnLine, vol. 51, no. 24, pp. 208–213, 2018.

Coandă, P. and Avram, M., State of art of predictive maintenance technique, IOP Conf. Ser.: Mater. Sci. Eng., vol. 997, no. 1, pp. 012039, 2020.

Crespo del Castillo, A. and Marcos, J. A., Dynamic fleet maintenance management model applied to rolling stock, Reliab. Eng. Syst. Saf., vol. 240, pp. 109607, 2023.

Daniyan, I. and Mpofu, K., Artificial intelligence for predictive maintenance in the railcar learning factories, Procedia Manuf., vol. 45, pp. 13–18, 2020.

Daniyan, I. and Mpofu, K., Implementation of artificial intelligence for maintenance operation in the rail industry, Procedia CIRP, vol. 109, pp. 449–453, 2022.

Daniyan, I. A. and Mpofu, K., Development of a diagnostic and prognostic tool for predictive maintenance in the railcar industry, Procedia CIRP, vol. 90, pp. 109–114, 2020.

Davari, N., Veloso, B., Costa, G. de Assis, P. M. Pereira, R. P. Ribeiro & J. Gama, "A Survey on Data-Driven Predictive Maintenance for the Railway Industry", Sensors, vol. 21, no. 17, 5739, 2021.

Dersin, P., Webinar: Prognostics & Health Management for Railways – Experience, Opportunities, Challenges, YouTube, 2020.

Foulliaron, J. and Bouillaut, L., A dynamic Bayesian network approach for prognosis computations on discrete state systems, J. Risk Reliab., vol. 231, no. 5, pp. 516–533, 2017.

Fumeo, E. and Oneto, L., Condition-based maintenance in railway transportation systems based on big data streaming analysis, Procedia Comput. Sci., vol. 53, pp. 437–446, 2015.

Gálvez, A. and Diez-Olivan, A., Fault detection and RUL estimation for railway HVAC systems using a hybrid model-based approach, Sustainability, vol. 13, no. 12, pp. 6828, 2021.

García-Méndez et al., An explainable machine learning framework for railway predictive maintenance using data streams from the Metro operator of Portugal, arXiv preprint arXiv:2508.05388, 2025.

Hadi, E. F. and Bin Baharuddin, M. Z., Advancing predictive maintenance: Median-based particle filtering in MOSFET prognostics, J. Eur. Syst. Autom., vol. 57, no. 4, pp. 1103–1117, 2024.

Kalapati, D., Credoz, A. and Staino, A., An AI-based Method for Predictive Maintenance of Railway Radio Communication Systems, IEEE 27th of ITSC, Edmonton, AB, Canada, pp. 2705–2710, 2024.

Kavitha, S. and Sesadri, U., A hybrid novel approach for rail wheel defect detection to ensure sustainability, Int. J. Transp. Dev. Integr., vol. 9, no. 1, pp. 181–187, 2025.

Lee, H. and Han, S.-Y., Generative adversarial network-based missing data handling and remaining useful life estimation for smart train control and monitoring systems, J. Adv. Transp., 2020.

Li, J. and Schaefer, D., A decision-based framework for predictive maintenance technique selection in Industry 4.0, Procedia CIRP, vol. 107, pp. 77–82, 2022.

Li, R. and Verhagen, W. J. C., Comparison of data-driven prognostics models: A process perspective, Proc. Eur. Saf. Reliab. Conf. (ESREL), pp. 1133–1140, 2020.

Li, Z. and He, Q., Prediction of railcar remaining useful life by multiple data source fusion, IEEE Trans. Intell. Transp. Syst., vol. 16, no. 4, pp. 2226–2235, 2015.

Liu, L. and Zhang, Z., Remaining useful life prediction for a catenary, utilizing Bayesian optimization of stacking, Electronics, vol. 12, no. 7, 2023.

Mitici, M. and others, Dynamic predictive maintenance for multiple components using data-driven probabilistic RUL prognostics: The case of turbofan engines, Reliab. Eng. Syst. Saf., vol. 234, pp. 109199, 2023.

Petersen, K. and Feldt, R., Systematic mapping studies in software engineering, Proc. Int. Conf. Eval. Assess. Softw. Eng., pp. 1–10, 2008.

Petersen, K. and Vakkalanka, S., Guidelines for conducting systematic mapping studies in software engineering: An update, Inf. Softw. Technol., vol. 64, pp. 1–18, 2015.
Salierno, G., Morvillo, S., Leonardi, L. & Cabri, G., An Architecture for Predictive Maintenance of Railway Points Based on Big Data Analytics, *Advanced Information Systems Engineering Workshops*, 29;382:29–40, 2020.
Shey-Huei, S. and Chin-Chih, C., Optimal preventive maintenance and repair policies for multi-state systems, Reliab. Eng. Syst. Saf., vol. 140, pp. 78–87, 2015.
Shimizu, M. and Perinpanayagam, S., Real-time prognostics and health management without run-to-failure data on railway assets, IEEE Access, vol. 11, pp. 28724–28734, 2023.
Soy, A. and Vij, D. P., AI-Powered Predictive Maintenance in Hybrid and Electric Rail Systems, International Journal of Basic and Applied Sciences, vol. 14, no. SI-1, pp. 13–17, 2025.
Wang, H. and Ye, X., Study on predictive maintenance strategy, Int. J. Sci. Technol., vol. 9, no. 4, pp. 295–300, 2016.
Wu, F. and Wu, Q., Useful life prediction based on deep learning: A survey, Sensors, vol. 24, no. 11, pp. 3454, 2024.
Zheng, Y. and Chen, W., Prediction of the remaining useful life of a switch machine, based on multi-source data, Sustainability, vol. 14, no. 21, pp. 14517, 2022.

Biographies

Driss EL HOR, is a PhD student at National School of Applied Sciences Ibn Tofail University. He receives 2 degree the first in Electrical Engineering from ENSA Kenitra, the second in Industrial Risk Management from INSA CVL-Bourges, France in 2021. His research interests include RAMS analysis, maintenance and electrical engineering.

Pr. Rachid BANNARI, is a full professor of applied mathematics and industrial engineering, recently director of the Engineering Sciences Laboratory at ENSA Kenitra. He receives a master degree in mathematics modeling from Bordeaux University in 2004. He had a PhD from Sherbrooke University Canada in 2009, in mathematic modeling and chemical engineering. He has more than 20 years of experience in academia and industry with various publications in different international journals, presentations at international conferences and research visits to international research centers.