



**HAL**  
open science

# PHM Development in Railways; Key Enablers and Challenges

Asma Ladj

► **To cite this version:**

Asma Ladj. PHM Development in Railways; Key Enablers and Challenges. 32nd European Safety and Reliability Conference, Aug 2022, Dublin, Ireland. pp.3087-3094, 10.3850/978-981-18-5183-4\_S30-02-352-cd . hal-04663760

**HAL Id: hal-04663760**

**<https://hal.science/hal-04663760v1>**

Submitted on 14 Nov 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# PHM development in railways: key enablers and challenges

Asma Ladj

*Railenium Research and Technology Institute, 59540 Valenciennes, France. E-mail: asma.ladj@railenium.eu*

In recent years, railways play a vital role in freight and passenger transport. As safety-critical systems, it is crucial to accurately detect and predict, as early as possible, any faults that may affect their operation. In this context, prognostic and health management (PHM) offers promising opportunities for the design and implementation of effective predictive maintenance strategy. To allow successful development of PHM in railway industry, it is important to study its key enabling technologies. Hence, we provide in this paper an overview of fundamental pillars for PHM deployment. This includes condition monitoring technologies, namely sensing and networking techniques. Besides, powerful methods for robust and accurate data processing based on artificial intelligence are presented. Moreover, we highlight barriers in railway PHM development, which should be addressed by both the research community and the industry.

*Keywords:* Railway industry, PHM, predictive maintenance, condition monitoring, artificial intelligence

## 1. Introduction

In transportation domain, the rapid growth in railroad traffic has prompted both researchers and managers to investigate promoting service quality (trains punctuality, travel comfort), maintenance cost-effectiveness, as well as avoidance of safety hazards. In this field, the reliability, availability, and maintainability (RAM) of critical railway components were extensively addressed in the literature. Indeed, any failure of such safety-critical systems can cause delays or potentially disastrous consequences (injuries, deaths) if no action is taken, such as the devastating Potters Bar accident (due to poorly maintained point machine at turnout)<sup>a</sup>. This reinforces and justifies the crucial need for the development of more reliable and more cost-effective maintenance strategies. The main prominent advancement was the shift from “find and fix” to “predict and prevent”. Thus, corrective and time-based maintenance are successfully replaced (or potentially completed) by condition-based maintenance (CBM). In this field, predictive maintenance, as a special form of CBM, has emerged as a part of the prognostics and health management (PHM) (Dersin et al., 2018).

The expansion of PHM in railway domain is

tightly related to the proliferation of several enabling technologies. Leveraging low-cost sensing solutions and maturity of Information and Communication Technologies (ICTs) have led to the emergence of internet of things (IoT) (Fraga-Lamas et al., 2017; Gbadamosi et al., 2021). In railway applications, condition monitoring systems (CMS), built using connected and smart devices, enable continuous and automated condition monitoring (CM) of critical components (Vinberg et al., 2018). CM covers, for example, dynamic impact load and wheel/rail defect monitoring, track superstructure and sub-grade monitoring, etc. Some successful industrial solutions are developed, such as Vossloh Cogifer’s SURVAIG NG for switches monitoring and Alstom’s “TrackTracer” fitted on service trains providing infrastructure monitoring.

CMSs are capable of measuring, among others key parameters, strain, displacement, acceleration, temperature, etc. As huge amount of data is currently easy to collect, conventional storage and computation capabilities overflow needs to be avoided through Big Data approaches. Big data provides powerful computing architectures (e.g., cloud computing) to manage voluminous data with no saturation neither response delays issues (McMahon et al., 2020). To derive useful insights from the raw data, Big Data Analytic

<sup>a</sup>Rail accident report: Derailment at grayrigg, 23 february 2007

uses advanced analytic techniques to make better understanding of the system and provide faster and better decisions (Thaduri et al., 2015). In this field, artificial intelligence (AI) technologies are gaining more attention from both researchers and infrastructure managers to exploit real-time monitoring data in decision-making support regarding predictive maintenance (Chenariyan Nakhaee et al., 2019). This is mainly achieved through development of advanced and efficient algorithms for failure diagnosis and prognosis, which provide opportunities to solve important challenges in reliability and maintenance engineering.

In this paper, the synergy between recent advances in both CM and AI tools and PHM development is investigated. The objective is to highlight the opportunities offered by exponentially growing technologies such as sensing, networking, IoT and AI for successful deployment of PHM in railway domain. This study allows also to rise challenging aspects which still need to be addressed.

The remainder of this paper is structured as follows: in section 2, key enablers for PHM in railway industry are outlined. First, CM development is discussed by presenting recent advances in sensing, networking, IoT technologies and existing CM applications. Next, we give insights into promising application of AI-based technologies for PHM tasks, mainly in fault diagnosis and prognosis. Section 3 highlights some challenges arising in deploying PHM solutions for railway systems. Finally, concluding remarks are drawn in Section 4.

## **2. Key enablers of railway PHM development**

PHM steps involve data acquisition, data pre-processing, detection, diagnostics and prognostics, decision making and finally human-machine interface (Atamuradov et al., 2017). Exponentially growing technologies are one of the fundamental pillars for PHM development. Such technologies, including ICTs, IoT, etc., are considerably helping to sharply increase PHM efficiency. In this section, the most important key enablers for PHM development, with focus on railway applications,

are presented.

### **2.1. Condition Monitoring**

Railway inspection operations are most often performed manually or visually by qualified personnel (Liu et al., 2019). These superficial checks may not be reliable to accurately diagnose and predict assets faults. Hence, this traditional policy should be replaced (or completed) by a more sophisticated and intelligent monitoring strategy. Thus, condition monitoring (CM) is recognized to be primordial for the effective management of railway systems. Indeed, real-time and autonomous monitoring is adopted as a powerful tool to improve railway systems safety and reliability by detecting and predicting deterioration of assets before causing failures, which reduces human inspection requirements and prevents costly and inopportune interventions Dersin et al. (2018). In the following sections we will briefly review recent advances in this field.

#### **2.1.1. Sensing technologies**

Data acquisition is the first step in any PHM process, which deals with data collection from the target system. Two types of data can be collected: CM or sensory data, which are measurements tracked via sensors installed on the system under investigation, and event data, which includes information of maintenance actions taken on the events (e.g. failure, breakdown, installation etc.).

Sensor technologies have undergone extensive developments. Different sensing techniques exist, ranging from simple transducers, converting the quantity to be sensed into an electrical signal that can be directly measured and processed, cheap and efficient micro electro mechanical systems (MEMS), combining electrical and mechanical components produced at relatively low cost, to innovative fiber optic sensors (FOS), with light weight, immunity to electromagnetic interference and corrosion, and high embedding capability. Depending on the measurement principle, sensors can be categorized to: mechanical sensors relying on direct physical contact, magnetic and electromagnetic sensors which do not require direct physical contact and are useful for detecting

proximity effects, optical Transducer converting light to various quantities, acoustic sensors using sound as a sensing medium, etc. A detailed review of these types can be found in (Lewis et al., 2004).

A variety of sensors are used in railway CM to measure key parameters of the assets. Measurements can be classified into: measurement of electrical parameters (current, voltage), measurement of motion properties (velocity, acceleration), measurement of contact properties (strain, force, vibration), measurement of presence (proximity, displacement, position), measurement of structural deformation (inclination), measurement of thermal parameters and environmental effects (temperature, moisture), sound and optical measurement. For example, we can use acoustic emission sensors for structural damage detection like crack and fatigue, accelerometers for infrastructure dynamic loads analysis as trains pass, strain gauges for static loads and stresses, inclinometers for structure distortion detection, etc. Since asset behavior is usually affected by external factors, it is crucial to take ambient measurements (e.g. temperature, humidity, wind speed and direction, train speed, etc.) into account when analyzing and interpreting CM data. The reader can refer to (Hodge et al., 2014; Ngamkhanong et al., 2018) for more details on sensors used in railway CM.

### 2.1.2. Networking technologies

In simple CM, sensors monitor the system health condition and generate alarms if the locally collected readings reach a predetermined fault threshold. To overcome this limitation, it is important to build an overall picture of the system condition by connecting the whole sensors deployed on the system and collectively analyze their data. In this context, ICT tools allow data transmission, storing, processing, interpretation and presentation.

Two options are available for data transmission: wired and wireless networking. In conventional wired technique, sensors are directly attached to the structure and cables connect them to the acquisition units. Communication protocols such as Ethernet and EtherCAT can be used. Although the results obtained with wired technique are accurate, this approach requires costly maintenance

interventions, as cables are vulnerable to damage (e.g., corrosion), weather conditions and nature elements, especially in harsh and exposed railway environment. Moreover, the wired system can become significantly complex when sensors number increases and inflexible when changes are needed. These shortcomings have led to the adoption of wireless networking as an alternative approach.

The wireless techniques becomes more competitive with increasing popularity (Hodge et al., 2014). In fact, this strategy can reduce the number of sensors, time for deployment, installation and maintenance costs and requires no special care to ensure safe placement of wires on the structure. Their biggest drawback is that, in general, the results obtained do not present the same level of accuracy when compared to those provided by wired techniques.

Several wireless communication technologies can be used: (i) *Peer-to-Peer technologies* such as Bluetooth Classic, (ii) *low-power / short-range / low-data Mesh technologies* such as Bluetooth LE (Low-Energy), ZigBee, (iii) *Local Area Network (LAN) technologies* such as WiFi, (iv) *long-distance cellular technologies* such as GSM (Global System for Mobile Communications), LTE (Long Term Evolution), and (v) *low-power Long-distance technologies* such as LoRa (Long Range), NB-IOT (Narrowband Internet of things).

The wireless communication strategy is used to build what we called wireless sensor networks (WSNs) (Hodge et al., 2014). WSNs can be used for monitoring the railway infrastructures such as bridges, rail tracks, track beds, and track equipment as well as rolling stock components health monitoring such as chassis, bogies, wheels, and wagons. WSN offers interesting opportunities compared with traditional inspection policy. It ensures continuous and high frequency monitoring (near real-time) where no supervision or human intervention is needed. Thanks to networking technologies, data accessibility and management are enhanced, and thus outcomes from the centralized processing of the whole integrated data of all sensor nodes are optimized. Indeed, smart nowcasting and forecasting algorithms, aiming to detect, diagnose and predict asset faults, since

the early stage, can be developed based on the efficient exploitation of collected data.

### 2.1.3. *IoT technologies*

With advancement in communication and computing technologies, as well as power and memory management, several civil applications have been digitized. In such innovative context, Internet of Things (IoT) has emerged as the combination of physical and digital components which connect and exchange data within the existing internet infrastructure (Fraga-Lamas et al., 2017).

One crucial objective of an effective railway maintenance is the ability to acquire useful and reliable information about asset health state. Indeed, such objective can be achieved using IoT paradigm. IoT offers opportunity for real-time CM of railway assets by ensuring the connectivity of IoT sensors Gbadamosi et al. (2021).

IoT sensors are mounted on boards combining a sensing module, a data processing module, a wireless module (e.g., NB-IoT), a power supply module, and eventually a GPS module (Zhao et al., 2020). An IoT sensor used for monitoring rail under excitation of wheels during trains passage using acceleration data was provided by Zhao et al. (2020). This sensor consists of a lithium battery, a power management, a microprocessor chip, a MEMS accelerometer, and a NB-IoT wireless transmission module. Low sampling rate, embedded data processing algorithms makes IoT sensors capable of efficiently realize real-time data analysis. However, for frequent sampling, the constrained resources of IoT sensors in term of microcontroller capabilities, power and memory fail. In this case, tools provided by big data analytics deployed using cloud computing allow to leverage the huge amount of data collected by IoT sensors by extracting useful information (Thaduri et al., 2015; McMahan et al., 2020).

One of the promising applications of IoT-based CM in railway domain is the Dynamic Maintenance Management System (DMMS) developed by Trenitalia in collaboration with SAP SE (Systemanalyse Programmentwicklung Societas Eu-

ropaea) <sup>b</sup>. Hundreds of sensors collect data in real time and upload them into SAP cloud, where they are analyzed and used to build predictive models using machine learning techniques and also trigger actions. Another example is represented by the Finnish state-owned railway company. In order to improve its competitiveness, it started to embed sensors into its systems to monitor possible failures related to the weather conditions <sup>c</sup>.

### 2.1.4. *Railway applications of condition monitoring*

Structural health monitoring (SHM) has been widely applied for detecting and predicting damage in railway infrastructures (Barke and Chiu, 2005). SHM goal is to reduce maintenance costs by the early detection of structures deterioration. Railway track structures often experience complex impact loading which cannot be reasonably calculated through mathematical models. Hence, monitoring of dynamic impact loads and wheel/rail irregularities is crucial to avoid hazardous derailments and dangerous accidents. Using dynamic load signals, wheel/rail defects (wheel flats, out-of-round wheels, wheel corrugation, etc.) can be detected (Ekberg et al., 2014). Besides CM of track superstructure, the track-bed (ballast and sub-ballast) and subgrade layer also need to be monitored as they play important roles in providing track stability and a smooth train ride (Ngamkhanong et al., 2017).

Apart from railway infrastructures monitoring, an interesting application of CM is vehicle parameters identification (Krc̃ et al., 2020). Actually, monitoring systems can be used to identify train type, axles count, train position and speed, etc (Krc̃ et al., 2020).

Regarding the data acquisition policy, CM can be either continuous or periodic. While continuous monitoring offers the possibility to timely detect abnormal events, high computing capabilities are needed to process sensor data for accurate fault diagnosis. On the other side, periodic monitoring is cheaper and requires less energy, but

<sup>b</sup>Trenitalia Dynamic Maintenance Management System

<sup>c</sup>The Internet of Trains

fault are not detected on time. Hence, regarding the targeted situation to be monitored, one or other strategy can be adopted. For example, in the case of long term and slowly developing degradation (e.g. railway structures cracks), periodic CM may be acceptable. Whereas, for time critical scenarios (e.g. obstruction in railway crossing), continuous monitoring becomes primordial.

Regarding the mobility of the sensor nodes, we can distinguish fixed and movable monitoring (Hodge et al., 2014). Fixed or trackside monitoring is built using sensor nodes mounted in fixed locations of railway infrastructures, to measure the whole train as it passes but only at points where the nodes are mounted. Movable or on-board monitoring relates to sensor nodes attached to the trains (Li et al., 2017). On-board sensors can monitor the sections of the train where the sensor nodes are attached (e.g. train engines, wagons, axles, wheels, etc.) (Kundu et al., 2018) as well as the whole track length travelled by the train (Dertimanis et al., 2020).

Several reviews on CMSs for railways are available. Hodge et al. (2014) reviewed the existing CM solutions from the perspective of fixed and movable monitoring, where systems are grouped according to the asset being monitored. Li et al. (2017) provide an overview of existing on-board monitoring techniques used for suspension and wheel–rail health monitoring. Vinberg et al. (2018) investigate and evaluate methods for CM in railway applications, with focus on the CM of vehicle running gear and track condition.

## 2.2. AI for railway PHM

Despite its huge volume, it is obvious that data collected through CM, on its own and without analysis, has no significant value regarding the health state of the asset under investigation. In fact, monitoring data usefulness is tightly related to the meaningful insights derived using data and big data analytics. Thus, railways raw monitoring data are transformed into smart data within the PHM process.

PHM assist decision making regarding predictive maintenance based on two tasks, namely fault diagnosis and prognosis. Diagnosis aims to detect,

isolate, and identify faults. On the other side, prognosis is the estimation of time to failure, known as the Remaining Useful Life (RUL) and risk for one or more existing and future failure modes (ISO, 2015). Prognosis is considered superior to diagnosis as it reduces costs by enabling faults or failures preventing and/or scheduling appropriate maintenance intervention in the right time (Niu, 2017). However, due to the unpredictable nature of some faults/failures, prognostics and diagnosis must be complementary.

Diagnosis and prognosis are developed using mainly three approaches: model-based, data-based and hybrid methods. Contrary to the model-based approaches where a priori knowledge about the system is needed, data-driven approaches require only a large amount of historical data. They use historical system measurements to assess degradation, detect possible faults and predict their evolution. With increasing complexity of civil engineering systems, it becomes crucial to develop new reliability analysis techniques which meet the industry increasing demand for precision and accuracy (Dersin et al., 2018). In this context, data-driven approaches are gaining a great attention and popularity due to the continuous development of reliable machine learning (ML) and deep learning (DL) solutions in the field of Artificial Intelligence (AI).

Studies dealing with data driven diagnosis and prognosis for predictive maintenance of railway assets are progressively receiving more attention. Xie et al. (2020) and Davari et al. (2021) provide extensive reviews on existing data-based techniques for handling railway predictive maintenance. From perspectives of the investigated railway system, most of studies focus on rail tracks, as one of critical railway components (Falamarzi et al., 2019; Chenariyan Nakhaee et al., 2019). Other railway infrastructures are also addressed, such as switch and crossings (Hamadache et al., 2019), track circuits (De Bruin et al., 2016), ballast (Ngamkhanong and Kaewunruen, 2022), bridges (Wedel and Marx, 2022), as well as trains components (Krummenacher et al., 2017).

Both ML and DL techniques are successfully applied to railway systems PHM

(Davari et al., 2021). Based on the availability of data and respective labels, ML methods can be classified into supervised learning, in which labeled training data sets, mapping predictor variables values to a correct target variable, are available, unsupervised learning, in which machine learns from data sets with no target variable, and semi-supervised learning, where only a subset of examples is labeled (Çinar et al., 2020). ML techniques such as support vector machines (SVM) and random forest (RF) are widely used for diagnosis (Gómez et al., 2020; Guo et al., 2021) and prognosis purposes (Atamuradov et al., 2018; Wang, 2021) in railway domain.

For voluminous and high dimensional data, ML-based algorithms show poor performance as they rely on domain knowledge and manual feature engineering. In this context, deep learning becomes more advantageous (Alom et al., 2019). DL can automatically learn hierarchical representations of large-scale data via deep neural networks, which makes it an effective tool for PHM applications (Rezaeianjouybari and Shang, 2020). Relatively less deep learning methods are used for railway assets PHM, we can quote the use of deep neural networks (DNN) (Zhao et al., 2017), convolutional neural network (CNN) (Peng and Jin, 2018), recurrent neural networks (RNN) (De Bruin et al., 2016), generative adversarial network (GAN) (Yao et al., 2020), etc.

### 3. Challenges in railways PHM development

As safety-critical systems, railways infrastructures require a predictive maintenance strategy with very high reliability due to potential catastrophic failure consequences. Despite the recent advances in key enablers technologies, many challenges are faced in railways PHM.

**Challenges with sensors selection for CM.** Selecting the appropriate sensor types to be used has a great importance. Indeed, identifying the key parameters of the targeted system to be measured, which allows efficient representation and assessment of system health state, is a major issue. Moreover, finding the optimal emplacement and

carefully located sensors for accurate data acquisition is crucial. Powering solutions also need to be considered as sensors are often installed away from energy supplies.

**Challenges with communication technologies selection.** As multiple networking technologies exist, it becomes important to carefully select the best choice regarding the situation to be monitored. Some factors must be considered, such as network robustness in harsh railway environment, real-time performance, range, bandwidth, network scalability, cost, security, reliability, and power consumption (Fraga-Lamas et al., 2017).

**Challenges with data for AI tools development.** The design of AI-based algorithms for PHM depends on the level of performance desired, data availability, quantity, dimension, balancing, and labelling, as well as the noise presented in the data. For instance, supervised machine learning techniques require availability and quality of a sufficiently large and labeled dataset. The labeling process of real-time data stream collected from sensors can be labor-intensive, expensive and requires a high level of expertise and domain knowledge (Chenariyan Nakhaee et al., 2019). Moreover, in most railway applications, only small number of abnormal (faulty) samples is available, which creates highly skewed distribution (Chenariyan Nakhaee et al., 2019). With such imbalanced classes, ML performance is affected. Another key issue is uncertainty presence, which influences accuracy of PHM outputs and may lead to false alarms or faults missing.

**Safety issues.** From the safety point of view, it is complicated to consider external sensors integration (either in railway infrastructures or rolling stocks), without performing a rigorous risk assessment process. In fact, sensors deployment may affect the nominal operation of railway assets (for example, trains components and signaling systems can be compromised by electronic devices due to electromagnetic compatibility issues). Moreover, wireless connectivity of CMS is vulnerable to outside interference, intrusion and cyber-attacks.

**Challenges with wide scale monitoring.** Despite the existence of some IoT-related technologies in the rail industry, there is still a lack of holistic implementation strategy for IoT (Gbadamosi et al., 2021), which must deal with communication technologies interoperability and integration into the information management system.

#### 4. Conclusion

This paper deals with PHM development in railway industry. First of all, enabling technologies from IoT, ICTs, and AI domains are discussed. Condition monitoring plays a major role in building effective predictive maintenance strategy. Key factors of the recent and rapid expansion in CM are the advances in sensing and networking technologies. In this field, WSNs based on Iot sensors are gaining a great importance due to their capabilities to provide continuous, autonomous, and near real-time data acquisition as well as to improve data accessibility and management. To efficiently exploit data generated through CM, AI-based methods for fault diagnosis and prognosis, as vital tasks for PHM, are applied. An overview of ML and DL approaches for predictive maintenance in multiple railway applications was provided. The current state of the art on PHM application in railway domain faces some challenges, which were briefly outlined. Future work can be considered to conduct more extensive study in this domain by means of morphological analysis to highlight more and less explored areas in this field.

#### Acknowledgement

This project has received funding from the Shift2Rail Joint Undertaking (JU) under grant agreement No 101012456. The JU receives support from the European Union's Horizon 2020 research and innovation programme and the Shift2Rail JU members other than the Union.

#### References

- Alom, M. Z., T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, M. Hasan, B. C. Van Essen, A. A. Awwal, and V. K. Asari (2019). A state-of-the-art survey on deep learning theory and architectures. *Electronics* 8(3), 292.
- Atamuradov, V., K. Medjaher, F. Camci, P. Dersin, and N. Zerhouni (2018). Railway point machine prognostics based on feature fusion and health state assessment. *IEEE Transactions on Instrumentation and Measurement* 68(8), 2691–2704.
- Atamuradov, V., K. Medjaher, P. Dersin, B. Lamoureux, and N. Zerhouni (2017). Prognostics and health management for maintenance practitioners—review, implementation and tools evaluation. *International Journal of Prognostics and Health Management* 8(3), 1–31.
- Barke, D. and W. K. Chiu (2005). Structural health monitoring in the railway industry: a review. *Structural Health Monitoring* 4(1), 81–93.
- Chenariyan Nakhaee, M., D. Hiemstra, M. Stoelinga, and M. v. Noort (2019). The recent applications of machine learning in rail track maintenance: A survey. In *International Conference on Reliability, Safety, and Security of Railway Systems*, pp. 91–105. Springer.
- Cinar, Z. M., A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. *Sustainability* 12(19), 8211.
- Davari, N., B. Veloso, G. d. A. Costa, P. M. Pereira, R. P. Ribeiro, and J. Gama (2021). A survey on data-driven predictive maintenance for the railway industry. *Sensors* 21(17), 5739.
- De Bruin, T., K. Verbert, and R. Babuska (2016). Railway track circuit fault diagnosis using recurrent neural networks. *IEEE transactions on neural networks and learning systems* 28(3), 523–533.
- Dersin, P., A. Alessi, O. Fink, B. Lamoureux, and M. Brahim (2018). Prognostics and health management in railways. In *Handbook of RAMS in Railway Systems*, pp. 79–98. CRC Press.
- Dertimanis, V. K., M. Zimmermann, F. Corman, and E. Chatzi (2020). On-board monitoring of rail roughness via axle box accelerations of revenue trains with uncertain dynamics. In *Model Validation and Uncertainty Quantification, Volume 3*, pp. 167–171. Springer.
- Ekberg, A., B. Åkesson, and E. Kabo (2014). Wheel/rail rolling contact fatigue—probe, predict, prevent. *Wear* 314(1-2), 2–12.
- Falamarzi, A., S. Moridpour, and M. Nazem (2019). A review of rail track degradation prediction models. *Australian Journal of Civil Engineering* 17(2), 152–166.
- Fraga-Lamas, P., T. M. Fernández-Caramés, and L. Castedo (2017). Towards the internet of smart trains: A review on industrial iot-connected railways. *Sensors* 17(6), 1457.
- Gbadamosi, A.-Q., L. O. Oyedele, J. M. D. Del-



- gado, H. Kusimo, L. Akanbi, O. Olawale, and N. Muhammed-yakubu (2021). Iot for predictive assets monitoring and maintenance: An implementation strategy for the uk rail industry. *Automation in Construction* 122, 103486.
- Go´mez, M. J., C. Castejo´n, E. Corral, and J. C. Garc´ıa-Prada (2020). Railway axle condition monitoring technique based on wavelet packet transform features and support vector machines. *Sensors* 20(12), 3575.
- Guo, G., X. Cui, and B. Du (2021). Random-forest machine learning approach for high-speed railway track slab deformation identification using track-side vibration monitoring. *Applied Sciences* 11(11), 4756.
- Hamadache, M., S. Dutta, O. Olaby, R. Ambur, E. Stewart, and R. Dixon (2019). On the fault detection and diagnosis of railway switch and crossing systems: An overview. *Applied Sciences* 9(23), 5129.
- Hodge, V. J., S. O’Keefe, M. Weeks, and A. Moulds (2014). Wireless sensor networks for condition monitoring in the railway industry: A survey. *IEEE Transactions on intelligent transportation systems* 16(3), 1088–1106.
- ISO (2015). 13381-1:2015 condition monitoring and diagnostics of machines — prognostics — part 1: General guidelines. *Int. Standard ISO 13381-1*.
- Krcˇ, R., J. Podrouzˇek, M. Kratochv´ılova´, I. Vukusˇicˇ, and O. Pla´sˇek (2020). Neural network-based train identification in railway switches and crossings using accelerometer data. *Journal of Advanced Transportation* 2020.
- Krummenacher, G., C. S. Ong, S. Koller, S. Kobayashi, and J. M. Buhmann (2017). Wheel defect detection with machine learning. *IEEE Transactions on Intelligent Transportation Systems* 19(4), 1176–1187.
- Kundu, P., A. K. Darpe, S. Singh, and K. Gupta (2018). A review on condition monitoring technologies for railway rolling stock. In *Proceedings of the PHM Society European Conference, Philadelphia, PA, USA*, Volume 13.
- Lewis, F. L. et al. (2004). Wireless sensor networks. *Smart environments: technologies, protocols, and applications* 11, 46.
- Li, C., S. Luo, C. Cole, and M. Spiriyagin (2017). An overview: modern techniques for railway vehicle on-board health monitoring systems. *Vehicle system dynamics* 55(7), 1045–1070.
- Liu, S., Q. Wang, and Y. Luo (2019). A review of applications of visual inspection technology based on image processing in the railway industry. *Transportation Safety and Environment* 1(3), 185–204.
- McMahon, P., T. Zhang, and R. Dwight (2020). Requirements for big data adoption for railway asset management. *IEEE Access* 8, 15543–15564.
- Ngamkhanong, C. and S. Kaewunruen (2022). Prediction of thermal-induced buckling failures of ballasted railway tracks using artificial neural network (ann). *International Journal of Structural Stability and Dynamics* 22(05), 2250049.
- Ngamkhanong, C., S. Kaewunruen, and C. Baniotopoulos (2017). A review on modelling and monitoring of railway ballast. *Structural monitoring and Maintenance* 4(3), 195.
- Ngamkhanong, C., S. Kaewunruen, and B. J. A. Costa (2018). State-of-the-art review of railway track resilience monitoring. *Infrastructures* 3(1), 3.
- Niu, G. (2017). *Data-driven technology for engineering systems health management*. Springer.
- Peng, X. and X. Jin (2018). Rail suspension system fault detection using deep semi-supervised feature extraction with one-class data. In *Proceedings of the Annual Conference of the PHM Society*, Volume 10, pp. 1–11.
- Rezaeianjouybari, B. and Y. Shang (2020). Deep learning for prognostics and health management: State of the art, challenges, and opportunities. *Measurement* 163, 107929.
- Thaduri, A., D. Galar, and U. Kumar (2015). Railway assets: A potential domain for big data analytics. *Procedia Computer Science* 53, 457–467.
- Vinberg, E. M., M. Martin, A. H. Firdaus, Y. Tang, and A. Qazizadeh (2018). Railway applications of condition monitoring. *KTH Royal Institute of Technology: Stockholm, Sweden*.
- Wang, W. (2021). Joint prediction of remaining useful life and failure type of train wheelsets: a multi-task learning approach. *arXiv preprint arXiv:2101.03497*.
- Wedel, F. and S. Marx (2022). Application of machine learning methods on real bridge monitoring data. *Engineering Structures* 250, 113365.
- Xie, J., J. Huang, C. Zeng, S.-H. Jiang, and N. Podlich (2020). Systematic literature review on data-driven models for predictive maintenance of railway track: Implications in geotechnical engineering. *Geosciences* 10(11), 425.
- Yao, D., Q. Sun, J. Yang, H. Liu, and J. Zhang (2020). Railway fastener fault diagnosis based on generative adversarial network and residual network model. *Shock and Vibration* 2020.
- Zhao, Y., Z. H. Guo, and J. M. Yan (2017). Vibration signal analysis and fault diagnosis of bogies of the high-speed train based on deep neural networks. *Journal of vibroengineering* 19(4), 2456–2474.
- Zhao, Y., X. Yu, M. Chen, M. Zhang, Y. Chen, X. Niu, X. Sha, Z. Zhan, and W. J. Li (2020). Continuous monitoring of train parameters using iot sensor and edge computing. *IEEE Sensors Journal* 21(14), 15458–15468.