Proceedings of the Sixth International Conference on
Railway Technology: Research, Development and Maintenance
Edited by: J. Pombo
Civil-Comp Conferences, Volume 7, Paper 7.12
Civil-Comp Press, Edinburgh, United Kingdom, 2024
ISSN: 2753-3239, doi: 10.4203/ccc.7.7.12

AI-Powered Singular Point Detection for Improved Energy Efficiency

R. Kour[1], N. Venkatesh[1], P. Dersin[1], V. Jägare[1], R. Karim[1], F. Le Corre[2] and H. Jarl[3]

[1]Division of Operation and Maintenance Engineering, Luleå University of Technology, Luleå, Sweden
[2]WCE Senior Expert Services, Alstom, France
[3]Fordonscontroller X-trafik, Tåg i Bergslagen AB, Stockholm, Sweden

Abstract

Globally, the railway is considered a sustainable and energy-efficient mode of transport. Recently, the utilisation of road transport has increased manifold due to loss of trust in railway transport. The situation is further aggravated by the inefficient use of resources, budgetary constraints, climate change, etc. Hence, there is a need to increase the capacity and punctuality of railway transport.

Therefore, this paper proposes a framework that can benefit the railway sector by facilitating the transition towards an energy-efficient railway system. This framework will achieve this by reducing unplanned stoppages, leading to increased punctuality, capacity, trust, and good governance.

One of the key challenges in achieving this goal is the ability to distinguish between a singular point (regular designed elements, like turnouts and joints) and actual track defects when using vibration measurements. To address this challenge, this paper focuses on applying Artificial Intelligent based techniques to identify and detect the existence of such regular designed elements.

This paper presents a case study of a measurement system installed in Sweden that provides a proof-of-concept for data fusion and data analytics using AI for improving the detection capability and thus increasing the prediction accuracy.

Keywords: track, singular points, artificial intelligent , railway, energy, maintenance.

1 Introduction

As per 2019 statistics in Sweden, the ratio of road and railway in energy usage is 30:1, in traffic is 7:1, and emissions are 111:1 [1]. As per 2014 statistics, the ratio of railway and road in cost of freight is 16:1 and passenger are 4:1. To accelerate railway as an energy-efficient means of transport, it is necessary to improve the punctuality and quality by efficient inspection and effective maintenance planning. The frequent defects, disturbances, and failures hinder the railway operation. Hence, there is a need to monitor & detect track defects and predict the occurrence of failures in the future for predictive maintenance.

Track discontinuities (turnouts, transition zones, switch joints, etc.) are placed along a railway track and are part of the track design [2]. Maintenance of these points, which are sometimes called "singular points" (SP) constitutes 8% of the total maintenance budget [3]. During measurements, these discontinuities can sometimes be confused with track defects. It is thus critical to distinguish between them to minimize false alarms. The main challenges are to detect precise localisation, especially when predictive maintenance is involved, and to keep false alarms rate to a low level.

The existing inspection vehicles frequency is quite low (every 2 months). Such inspections are expensive and hinder normal traffic.

Some attempts have been made at detecting singular points (SP) and distinguishing them from defects by using onboard sensors. Processing of data acquiring from such sensors can resort to several of the numerous techniques developed over the years and described in the literature; for instance, the Bayesian approach [2], [4], Hidden Markov Models [5], signature analysis [7], and numerical analysis [8]-[11]. Other approaches use Smartphone measurements [6] for railway track quality detection and experimental measurements [12], [13] for faults detection.

Among the works surveyed, only Paixao, et al [14], combined data from track measurement with smartphones for detection of discontinuities. Some researchers applied AI and ML for detecting track discontinuities [15]-[17]. The early detection of track defects will reduce the probability of failures thus reducing the energy consumption [18]-[22].

In addition, there are several other data sources available to distinguish between defects and discontinuities, such as LIDAR [23], INSAR [24], infrastructure data, etc. However, the root cause of defects might be also because of various reasons such as weather parameters. Therefore, a framework is needed to integrate all existing datasets through data fusion and leverage AI-powered data analytics. This will enhance detection capability and consequently improve prediction accuracy. The hypothesis is that this framework will benefit the railway sector by enabling a shift to a more energy-efficient railway system. It is expected to achieve this by reducing unplanned stoppages, leading to increased punctuality, capacity and trust.

2 Methods

The initial step involved consists of designing the integration of the measurement system. This system comprises of electrical and mechanical components, including an accelerometer sensor mounted on the train's axle box for vibration monitoring. The accelerometers were placed on the front axle right and rear axle left positions. Sample pictures of the Alstom Track Tracer, which measures vertical acceleration, are provided in Figure 1.

Installing onboard equipment on a train requires a safety risk assessment following the 'Common Safety Method for Risk Evaluation and Assessment (CSM-RA)'. This assessment requires collaboration between the train manufacturer, operator, and owner. Upon successful completion of the risk assessment, the sensor will be installed on the trainset.

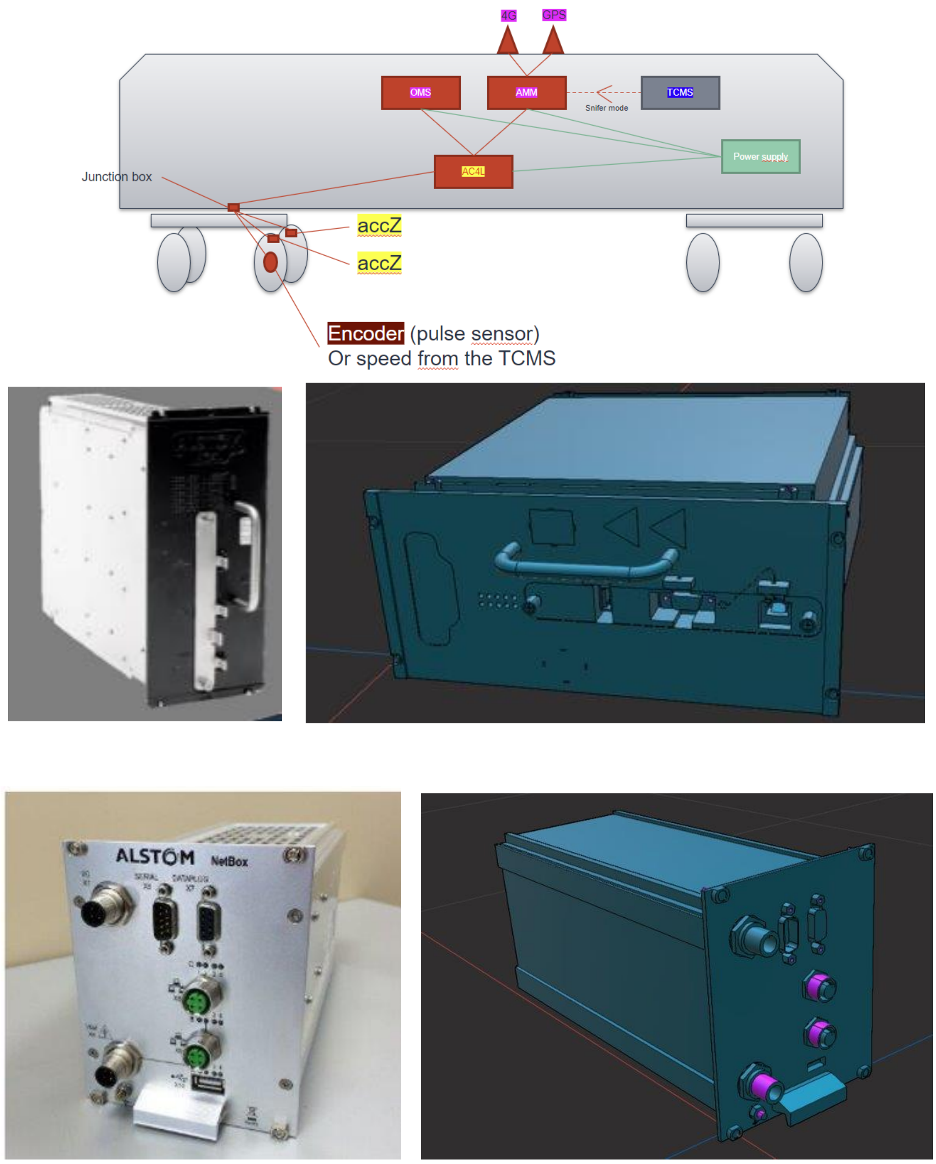


Figure 1. Sample pictures from the Alstom about the Track Tracer

The next step involves utilizing a cloud-based digital platform called AI Factory for Railway (AIF/R) [25]. AIF/R offers capabilities such as acquiring, integrating, transforming, and processing data (in our case, vibration data). Data analysis within

AIF/R helps ensure railway safety, sustainability, and profitability. AIF/R's analytical engines and AI-based algorithms facilitate real-time data stream and complex event processing to support prescriptive analysis for asset health monitoring and optimized planning. AIF/R's integrated services can be invoked on-premises or in multiple cloud environments. The AIF/R architecture is built on loosely coupled storage and computing services (see Figure 2).

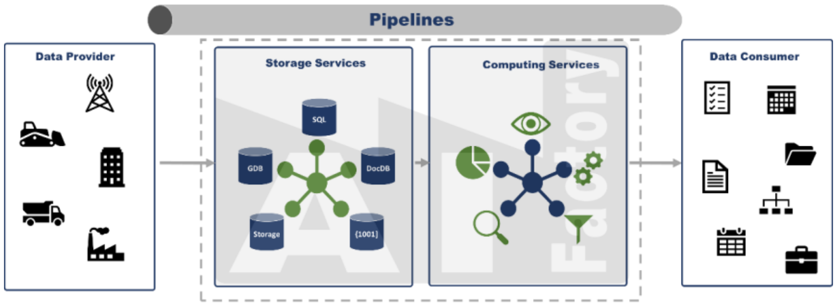


Figure 2. AIF/R's conceptual architecture [25]

AIF/R will implement digital pipelines between data providers and data consumers. Each pipeline represents a set of orchestrated activities aimed to extract, transfer, load, and process datasets between the provider and the consumer. AIF/R’s pipelines are configurable entities, which can utilise a palette of technologies e.g., communication, storage, and processing, to enable context-adaptability and fulfil the users’ requirements.

The objective of the present study revolves around the determination of SP contacts, namely, switches and turnouts, with the help of vibration signals collected. Furthermore, the study can be extended in identifying track defects by determining the maximum vibration threshold that can help in distinguishing among the singular point contacts and actual track defects. Within the context of this paper, authors have attempted to use methods like one class support vector machines to distinguish among the normal operation and single point contacts wherein the classifier can be trained using a single class (normal operation) that can aid in determining SP of contacts when evaluated.

3 Results

This paper proposes a framework based on Condition Based Maintenance (CBM) principles (see Figure 3). The Open System Architecture for Condition-Based Maintenance (OSA-CBM) [26] defines this framework, following the ISO-13374 standard [27] for track health monitoring. OSA-CBM serves as the foundation for implementing CBM through this framework, promoting a modular system design for interoperability between railway-specific CBM components, such as track monitoring sensors, data acquisition modules, and diagnostic tools. A brief description of each of OSA-CBM's seven layers in the context of railway track health monitoring is provided.

Data Acquisition: This layer gathers data from accelerometer sensors and feeds it into the CBM system.

Data Manipulation: This layer preprocesses the raw vibration data for analysis. Common techniques include data cleaning, feature selection, extraction, and standardization.
State Detection: This layer compares vibration data with predefined thresholds. If these thresholds are exceeded, an alert is triggered to signal potential issues.

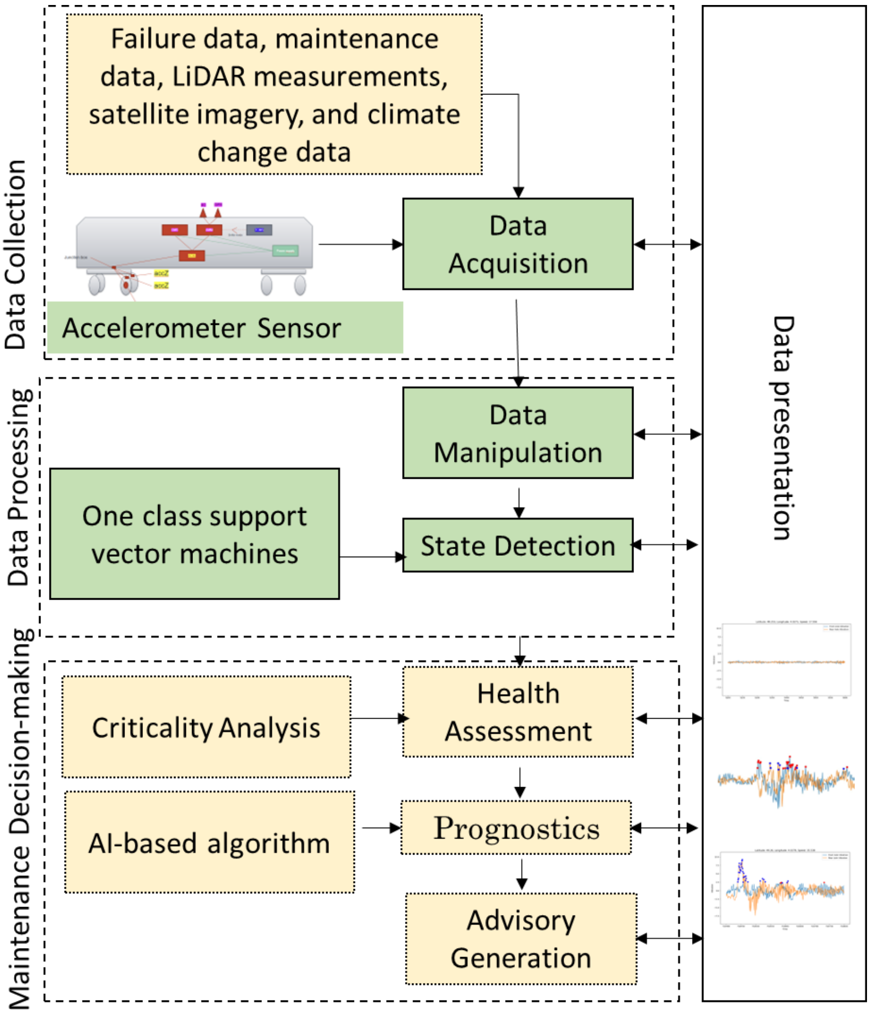


Figure 3. AI-based framework for predictive maintenance adapted from (OSA-CBM) [26] (will be updated continuously)

Health Assessment: This layer focuses on determining whether the health of the monitored track has deteriorated. It generates diagnostic records and proposes potential fault locations.
Prognostics: This layer focuses on estimating the future health of the track and predicting the remaining useful life (RUL).
Advisory Generation: This layer generates recommended actions based on the predicted future states of the track.
Presentation: This layer provides an interactive human-machine interface (HMI) to visualize relevant data, information, and results obtained in previous steps.

This paper focuses on the work represented by the green block in Figure 3, which is identifying and detecting the existence of SP on the track. Future work, represented by the yellow blocks, will focus on differentiating between these SP and defects in their vicinity on the track.
To validate this framework, a case study has been considered. The vibration data used in this case study came from accelerometer sensor affixed on the front right side and rear left side of the wagon. The vibration data was collected from the sensor for every 0.0005s alongside the global positioning system that collected the latitude, longitude and speed values for every 0.2s. Two files of vibration data contains 7200001 rows and one column for every sensor affixed on the front right side and rear left side of the wagon. While the latitude, longitude and speed were collected in three different files with 18000 rows and one column. The collected data was synchronous and required preprocessing to match between the vibration data and corresponding latitude, longitude and speed values. The data was collected between two tram stations and the path utilized is presented in Figure 4.

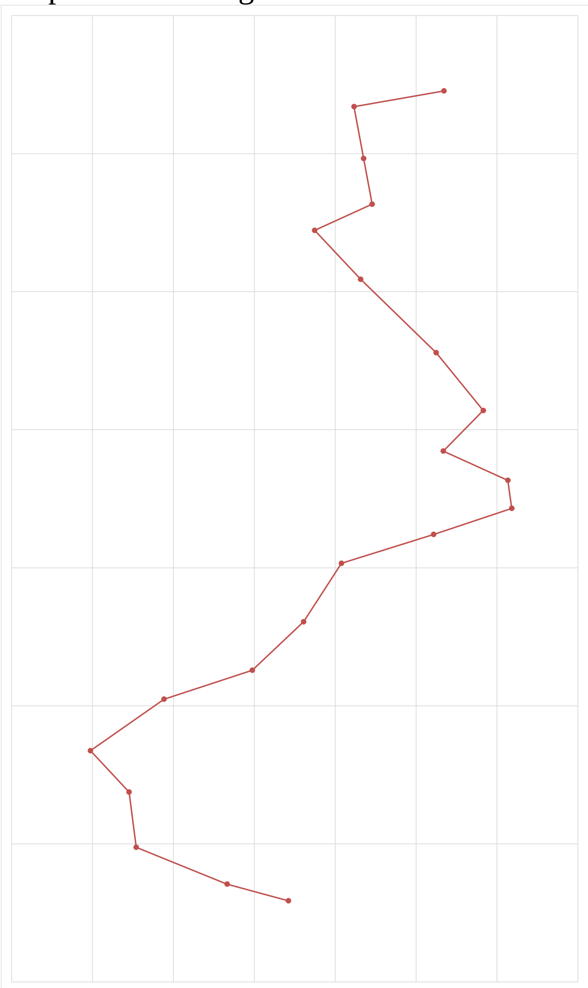
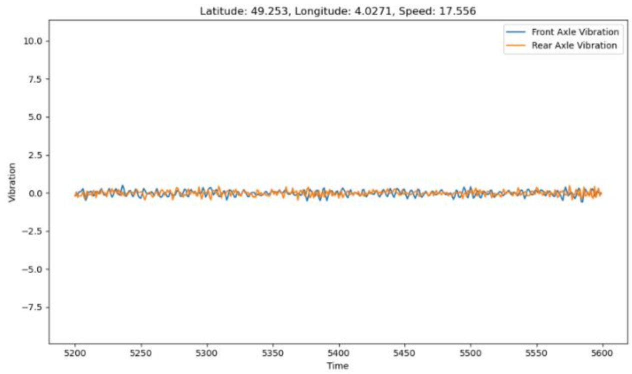


Figure 4 Anonymous Travel route of the tram

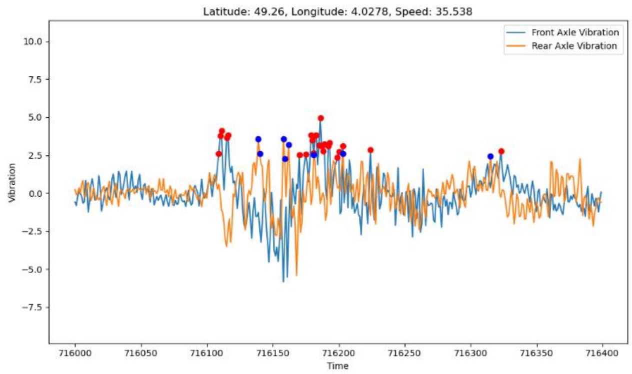
The following steps were utilized to carry out the preprocessing of data and identify possible direction for research.

- Since the data was non-synchronous, a data preprocessing was required to synchronize the vibration data with respect to the corresponding latitude and longitude pair. Thus, the window for total vibration signals for every corresponding pair of latitude and longitude was identified as 400.
- Post identification of the window size, an attempt was made to plot the vibration signals across the entire range of latitude and longitude pair. A total of 18000 plots were derived, which was challenging to analyse.
- However, based on the discussion with railway experts, a threshold-based methodology was suggested wherein, the vibration values that fall outside 20% of the maximum vibration value were identified and plotted along with the corresponding latitude and longitude values (See, Figure 5).
- Through this process the number of plots were narrowed down to 720 plots. With the aid of look up tables, latitude and longitude values of switches and turnouts were identified and filtered from the actual data.
- To automate the process of identification, the authors are still working on the process to extract the normal operating conditions from the switches and turn outs to train the one class support vector machine classifier.

The plots showing normal operating conditions and abnormal operating conditions (either singular points or faults) are presented in Figure 5.



(a)



(b)

Figure 5 Vibration plots representing (a) normal operation, (b) peaks signifying abnormal operation

In future, we will apply one- class support vector machine classifier to distinguish among the normal and abnormal operating scenarios. One class support vector machine is a type of support vector machine that has been widely adopted in the field of defect detection. One class support vector machine unlike conventional support vector machines is primarily designed for estimating the support provided for higher dimension distribution. One class support vector machine classifier during the process of training constructs a hypersphere instead of a hyperplane for the set of training points fed as input. Based on the creation of hypersphere, the classifier can draw the boundaries among the anomalies and outliers for the new data supplied post the training phase. The new data point is classified as normal or abnormal depending upon the region the data point falls i.e., inliers or outliers. Inliers are generally depicted as normal while outliers are depicted as abnormal. The performance of the one class classifier can be highly impacted with the selection of hyperparameters like nu (number of samples), kernel function and various associated parameters. Overall, one class support vector machine is a powerful tool that can provide significant insights to the present problem at hand. Additionally, we will also investigate other approaches along with SVM to determine singular points.

4 Conclusions and future directions

It has been concluded that a holistic framework based on OSA-CBM using AI based techniques helps to identify and detect the existence of SP on track. This framework can further help to differentiate between these detected track elements and track defects to enable predictive maintenance. Future directions involve integrating various data sources, including, track measurements, failure data, maintenance data, LiDAR measurements, satellite imagery, and climate change data. This comprehensive approach will enable us to compare results from diverse sources and develop more robust and reliable predictive models for detecting the presence of regular designed elements and associated defects.

Acknowledgements

The authors would like to acknowledge the funding provided by Energimyndigheten and the support from JVTC (Luleå Railway Research Center) in facilitating railway companies' participation within the AIF/R project framework.

References

[1] I. Vierth, R. Karlsson, T. Linde and K. Cullinane, "How to achieve less emissions from freight transport in *Sweden," *Maritime Business Review*, vol. 4, no. 1, pp. 4-15 2019.

[2] E. Cme, L. Bouillaut, P. Aknin and S. Allou, "Bayesian network for railway infrastructure diagnosis," *Proceedings of Information Processing with Management of Uncertainty in Knowledge-based Systems (IPMU'06)* 2006.

[3] J.N.V. da Silva Ferreira, "No title," *Long-Term Behaviour of Railway Transitions under Dynamic Loading Application to Soft Soil Sites* 2013.

[4] L. Oukhellou, E. Come, L. Bouillaut and P. Aknin, "Combined use of sensor data and structural knowledge processed by bayesian network: Application to a railway diagnosis aid scheme," *Transportation Research Part C: Emerging Technologies*, vol. 16, no. 6, pp. 755-767 2008.
[5] E. Côme, L. Bouillaut, P. Aknin and L. Oukhellou, "Hidden markov random field, an application to railway infrastructure diagnosis," *IFAC Proceedings Volumes*, vol. 40, no. 6, pp. 13-18 2007.
[6] A. Rodriguez, R. Sanudo, M. Miranda, A. Gomez and J. Benavente, "Smartphones and tablets applications in railways, ride comfort and track quality. transition zones analysis," *Measurement*, vol. 182, pp. 109644 2021.
[7] D.M. Steffens, "Identification and development of a model of railway track dynamic behaviour, 2005," 2005.
[8] G. Kouroussis, K.E. Vogiatzis and D.P. Connolly, "A combined numerical/experimental prediction method for urban railway vibration," *Soil Dyn.Earthquake Eng.*, vol. 97, pp. 377-386 2017.
[9] H. Askarinejad and M. Dhanasekar, "A multi-body dynamic model for analysis of localized track responses in vicinity of rail discontinuities,", vol. 16, no. 09, pp. 1550058 2016.
[10] G. Kouroussis, D.P. Connolly, G. Alexandrou and K. Vogiatzis, "Railway ground vibrations induced by wheel and rail singular defects," *Veh.Syst.Dyn.*, vol. 53, no. 10, pp. 1500-1519 2015.
[11] D.J. Thompson, G. Kouroussis and E. Ntotsios, "Modelling, simulation and evaluation of ground vibration caused by rail vehicles," *Veh.Syst.Dyn.*, vol. 57, no. 7, pp. 936-983 2019.
[12] F. Espinosa, Á Hernández, M. Mazo, J. Ureña, M.C. Pérez, J.A. Jiménez, I. Fernández, J.C. García and J.J. García, "Detector of electrical discontinuity of rails in double-track railway lines: Electronic system and measurement methodology,", vol. 18, no. 4, pp. 743-755 2016.
[13] R. Shafique, H. Siddiqui, F. Rustam, S. Ullah, M.A. Siddique, E. Lee, I. Ashraf and S. Dudley, "A novel approach to railway track faults detection using acoustic analysis,", vol. 21, no. 18, pp. 6221 2021.
[14] A. Paixão, E. Fortunato and R. Calçada, "Smartphone's sensing capabilities for on-board railway track monitoring: Structural performance and geometrical degradation assessment,", vol. 2019 2019.
[15] F. Carlvik, "Detection of rail squats from axle box acceleration: Optimization of a machine learning algorithm," 2020.
[16] C. Yang, Y. Sun, C. Ladubec and Y. Liu, "Developing machine learning-based models for railway inspection,", vol. 11, no. 1, pp. 13 2020.
[17] A. Gaikwad, B. Giera, G.M. Guss, J. Forien, M.J. Matthews and P. Rao, "Heterogeneous sensing and scientific machine learning for quality assurance in laser powder bed fusion–A single-track study,", vol. 36, pp. 101659 2020.
[18] G.M. Scheepmaker, H.Y. Willeboordse, J.H. Hoogenraad, R.S. Luijt and R.M. Goverde, "Comparing train driving strategies on multiple key performance indicators,", vol. 13, pp. 100163 2020.

[19] D. Basile, F. Di Giandomenico and S. Gnesi, "On quantitative assessment of reliability and energy consumption indicators in railway systems,", pp. 423-447 2019.

[20] G.L. Nicholson, D. Kirkwood, C. Roberts and F. Schmid, "Benchmarking and evaluation of railway operations performance,", vol. 5, no. 4, pp. 274-293 2015.

[21] M. Miyatake and H. Ko, "Optimization of train speed profile for minimum energy consumption,", vol. 5, no. 3, pp. 263-269 2010.

[22] P. Norrbin, J. Lin and A. Parida, "Energy efficiency optimization for railway switches & crossings: a case study in Sweden," in *World Congress of Railway Research: 29/05/2016-02/06/2016*, 2016.

[23] W. Zhangyu, Y. Guizhen, W. Xinkai, L. Haoran and L. Da, "A camera and LiDAR data fusion method for railway object detection,", vol. 21, no. 12, pp. 13442-13454 2021.

[24] L. Bianchini Ciampoli, V. Gagliardi, C. Clementini, D. Latini, F. Del Frate and A. Benedetto, "Transport infrastructure monitoring by InSAR and GPR data fusion," *Surv.Geophys.*, vol. 41, pp. 371-394 2020.

[25] R. Karim, D. Galar and U. Kumar, *AI factory: theories, applications and case studies*, CRC Press, 2023.

[26] OSA-CBM. *MIMOSA OSA-CBM – Open System Architecture for Condition-Based Maintenance* [Online]. available: https://www.mimosa.org/mimosa-osa-cbm/.

[27] ISO. *ISO 13374, Condition monitoring and diagnostics of machine systems — Data processing, communication and presentation* [Online].