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Review

REVIEW

Artificial Intelligence in Railway Infrastructure: Current Research, Challenges, and Future Opportunities

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Abstract

The railway industry has the potential to strongly contribute to achieving various sustainable development goals by expanding its role in the transportation system of different countries. To realize that, complex technological and societal challenges are to be addressed, along with the development of suitable state-of-the-art methodologies fully tailored to the particular needs of the wide variety of railway infrastructure types and conditions. Artificial intelligence (AI) methods have been increasingly and successfully applied to solve practical problems in the railway infrastructure domain for over two decades. This paper proposes a review of the development of AI methods in railway infrastructure. First, we present a survey limited to selected journal papers published between 2010-2022. Bibliographical statistics are obtained, showing the increasing number of contributions in this field. Then, we select key AI methodologies and discuss their applications in the railway infrastructure. Next, AI methods for key railway components are analyzed. Finally, current challenges and future opportunities are discussed.

Key words: Railway Infrastructure, Artificial Intelligence, Machine Learning, Railway Track, Railway Catenary, Digitalization

1. Introduction

Industrial sectors have been increasingly limiting the use of fossil fuel consumption. However, transport sectors still struggle to significantly reduce CO_2 emissions. With the current technological progress, the road sector cannot cope with the challenge despite the environmental standards and the development and steady improvement of alternative fuel vehicles (37). Increasing rail usage in the modal share between rail and road transport is envisioned as an important strategy when developing greener and more sustainable societies (51). In some countries, this can be achieved by equipping more regions with new railway networks and infrastructures. In other countries where railway infrastructure is already densely used, increasing the effectiveness of their operations, the level of satisfaction of users, and the optimal use of resources are major challenges.

Rail sectors in Europe aim to reduce CO_2 emissions for passenger and freight transport by 30% from 1990 by 2030. However, more regions equipped with railway tracks and more intense use of the infrastructure imply higher degradation rates and a higher likelihood of facing disruptions. As trains run on the track, the quality of railway infrastructure gradually deteriorates over time. When this deterioration is not under control, it can cause disastrous events, e.g., broken rails, train derailment, etc (91). Thus, railway infrastructure must be kept in acceptable condition under all sorts of different scenarios of degradation mechanisms, considering the most updated knowledge about the particular types of failures in all the components and their consequences. Further, in highly used networks, disruption might affect many passenger and freight transports. Thus it is crucial to not only prevent safety issues but to keep the trust of users in the reliability of services so that rail users do not shift to other transportation modes (18).

Generally, railway assets can be grouped into two main types: the infrastructures and the rolling stock. Railway infrastructures include tracks, tunnels, bridges, and catenary systems. Rolling stock refers to assets that can move on a railway network, and examples are locomotives, passenger coaches, and freight cars. Common problems affecting these assets can include failures with origin in the usage of infrastructure components (such as rail defects), failures in the rolling stock (such as door opening failures), and events due to exogenous factors such as third parties (e.g., collisions with persons at stations and non-authorized/trespassing people on railway properties) and weather conditions (such as flooding). The railway industry has been dealing with those problems mostly by relying on traditional approaches. Still, some examples from the industry about the use of artificial intelligence (AI) in railway applications have been reported. Just to mention some, there are monitoring systems of the infrastructures powered by AI to monitor the status of bridges, tunnels, switches, and energy systems. Other reported examples of sensing technologies enhanced by AI include line-scan sensors and cameras from passenger trains, and fiber optic acoustic sensors to detect rail and wheel defects, trespassers, and level crossings. AI-based algorithms relying on wayside train monitoring systems have been developed for damage detection of pantographs, wheels, and brake blocks. Furthermore, AI has also been exploited for robust rail logistic planning. However, the use of AI in railway environments is not yet the standard. This indicates that further developments are needed before reaching a maturity level to be ready to implement reliable solutions under a large variety of infrastructures. While the current developments in the industry are interesting to analyze as they give indications on the acceptance level of AI solutions, in this paper, we focus on the advancements in AI solutions reported in journal publications. Our target is to provide an overview of developments and discuss gaps and future opportunities that can support understanding the use of AI technologies in railway infrastructure.

Our review primarily focuses on publications dealing with four selected groups of railway infrastructures as illustrated in Figure 1. The selected groups comprise railway track (rails, welds, joints, switches, fastening systems, ballast, crossings, and sleepers), railway catenary (catenary and pantograph), railway civil structures (tunnels, bridges, viaducts, culverts), and railway substructures (subgrade, soil, and embankments). The reason is that these infrastructures form the foundation for safety, quality and reliability of services, and long-term costs. Moreover, by proactively identifying and addressing degradation-related failures, risks can be minimized and a safe railway systems can be ensured. Therefore, the focus is on their failures arising from degradation and usage. Rolling stock, railway signaling, and operations are excluded from our review. Interested readers in other railway topics are referred to other recent reviews such as (43; 14; 138; 107).

Railway infrastructure is a highly complex distributed parameter system. In other words, the dynamic characteristics of the railway infrastructure change over time and space. The changes over time refer mainly to the consequences due to its continuous usage, degradation processes, and human interventions such as maintenance. The changes over space refer to the fact that governing dynamics are different per location; for instance, railway tracks at bridges, tunnels, stations, and curves behave differently than straight tracks. Although the railway infrastructure can also be seen as a line structure with some components presenting a sort of local periodicity (such as the sleeper spacing), the substructure and structure track parameters are unique at each location. Additionally, the railway infrastructure is subject to various sources of stochasticity that can affect its functionality, such as weather conditions. Thus, the railway infrastructure is a dynamic, continuous, distributed, and stochastic system that is fundamentally challenging, and from where the need to develop new intelligent methods that can be tailored to practical solutions at a local level naturally appears.

The optimal use of railway infrastructure requires holistic approaches to its management that explicitly include the complex interlinks among infrastructure, society, and the environment. Railway infrastructure research is inherently multidisciplinary. Answering fundamental questions in this field requires not only knowledge of its physical responses (structural, mechanical, etc.). We also need to understand the limitations of selected mathematical modeling approaches, the capabilities of state-of-the-art measurement technologies (vibration, images, laser, etc.), the maintenance technology available, the behavior of stochastic variables (weather, reliability, etc.), the inclusion of the human aspects regarding users and workers, and the complex interlinks between railway governance and contracts, etc. It appears that the problems associated with railway infrastructure are unique to different places and times. This opens up many opportunities to develop a variety of new intelligent solutions to capture the essential characteristics of the infrastructure and to provide solutions that traditional methods cannot truly provide.

Health condition monitoring and maintenance play a vital role in ensuring the safety, availability, and reliability of

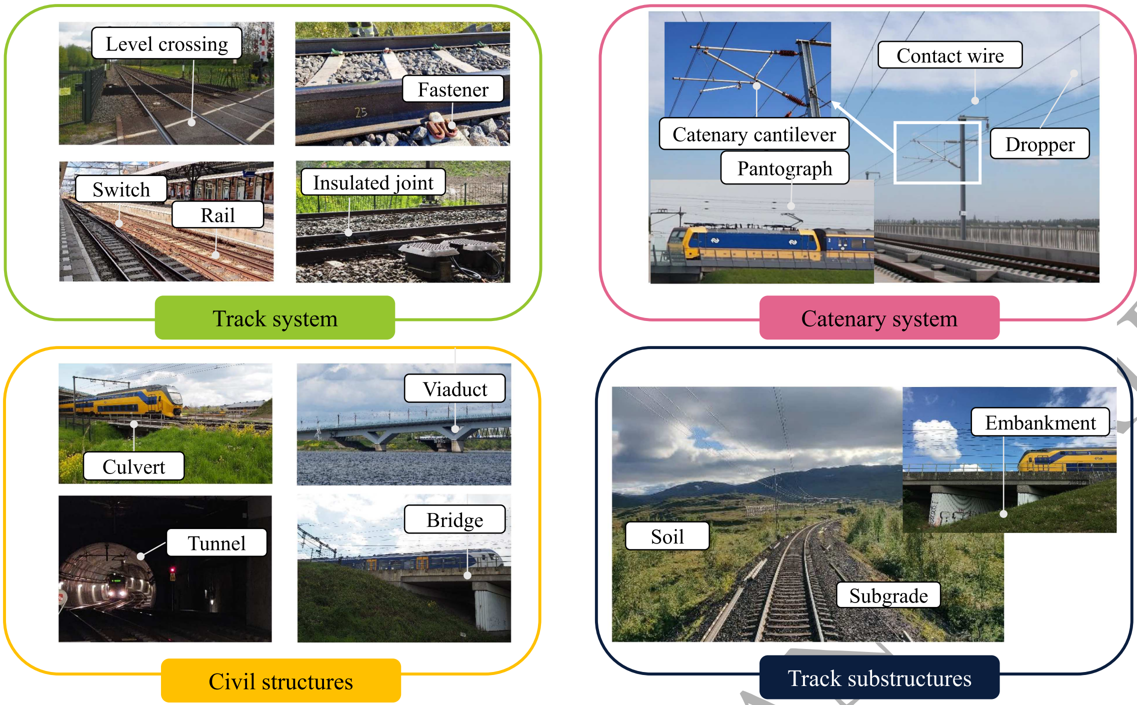


Fig. 1. Illustration of the four selected groups of railway infrastructures considered in this work: track system, catenary system, civil structures, and track substructures.

service simultaneously and in prolonging the life span of the infrastructure. Early detection and preventive maintenance of possible failures before they occur have shown great potential for cost savings (104; 133). The continuous monitoring of critical components has not only increased the level of safety but drastically increased the availability of the infrastructure, as early warning systems allow to include the repairs or replacement of these components during the routine maintenance slots. Therefore, the railway industry and researchers from various countries have been developing integrated and robust approaches to continuously monitor and maintain railway infrastructures (160; 15; 68; 123; 87). With the developments in sensors and information technology, health conditions in railway infrastructure get monitored continually by using sensors installed in the rolling stock (e.g., rail and pantograph monitoring), in areas adjacent to the track (e.g., switch engine monitoring), and crowd sensing (e.g., with mobile phones that measure vibrations, temperature, pressure, etc.). Monitoring of railway systems has the potential to support the management of their performance. Yet, how to respond to the daily detection of faults poses another problem for inframanagers due to limited resources, short closure times, lack of alternative routes, and the standards that rely on time-based inspection. Additionally, databases constructed from continuous data monitoring become larger over time, which poses a challenge to their transmission, storage, and analytics. For instance, when using onboard axle box acceleration systems and laser Doppler vibrometers, an open challenge is how to migrate such high-frequency sampling data onto any cloud and database due to the limitation of the existing communication bandwidth. To reduce the amount of data, data pre-processing and analytics on-premise can be an option. Further, new standards are still required when dealing with multiple measurement sources and new sensing technologies, e.g., satellite data. All in all, the railway industry and academia have been working to address these challenging issues in which further cooperation can unlock the best solutions and overcome these barriers to the adoption of AI.

Thus, advanced railway networks, in essence, require standardization and governance for big data management and analytics to monitor the infrastructure condition and control life cycle costs adequately (43; 93). In the literature, sophisticated data management for data storage and analytics has proven to enable the development of better railway maintenance solutions. This is because big data analytics enables asset managers to switch from reactive maintenance towards predictive maintenance (26). The literature on data analytics (114; 7; 141) shows that artificial intelligence (AI) is increasingly popular in various domains as it allows automation in decision support tools by linking data with decisions and enabling asset-specific and whole system behavior analyses. This paper focuses on AI applications in railway infrastructure, including technologies, methods, and models in AI that have been published concerning monitoring, diagnosis, prognosis, detection, classification, and maintenance. The paper is structured as follows. In the next section, we conduct a bibliographical analysis to identify the most used and promising AI methodologies in the field of railway infrastructure. Then, we discuss how these methods have been adapted to railway environments for tackling different challenges. Given the dense literature, we describe a few selected characteristic examples of these AI methods and railway applications. Finally, we discuss open challenges and opportunities for the development of AI in the asset management of railway infrastructures.

2. Bibliographical analysis

Artificial intelligence (AI) refers to developing computer systems and machines that can replicate or simulate human cognitive abilities. AI involves the creation of algorithms and models that allow computer systems and machines to understand natural language, to recognize patterns, to solve problems, to make decisions, and to adapt to new situations. AI has been deployed in railway applications for decades. Some of the first works reported in the literature of railways that explicitly mention AI in the eighties are in the fields of diesel-electric locomotives using expert systems (63) and derailment analysis (55). For neural networks, the first applications reported in the early nineties were in traffic management (45) and rail defects using ultrasonic images (92), among others. Nowadays, AI plays an essential role in analyzing characteristics of complex railway measurements and in identifying relevant patterns amongst an abundance of information. Many intelligent systems relying on AI technologies have been developed and integrated into railway infrastructure to tackle problems arising from its usage and natural degradation mechanisms. To select these topics, a first broad bibliographical search was conducted from where the more prominent fields and recent trends were selected, including neural networks, metaheuristics, regression (supervised), probabilistic graphical models, fuzzy logic, clustering (unsupervised learning), and transfer learning.

The bibliographical search is conducted over papers published within the context of AI and railway infrastructure. We consider the track system, catenary-pantograph system, civil structures, and substructure. Papers about rolling stock, railway signaling, and operations are excluded from the analysis. The review aims at papers in scientific journals considering both article and review types of documents. The publication years considered are from 2010 to 2022. Only papers in English and the engineering subject area are included (which will leave out papers at the interfaces with other domains). Scopus is chosen as the citation database, and the precise search terms are considered in conjunction with the generic words to capture most documents of our interest. The search terms are incorporated into three groups as presented in Table 1.

2.1. Paper retrieving process

The search is restricted to fields in the article title, abstract, and keywords. As shown in Table 1, the wildcard asterisk is employed to include plurals and spelling variants. Likewise, the double quote, , is used to search for vague phrases in which symbols are ignored. To search for papers using AI methodologies in railway infrastructure, the associated search terms from Group 1, Group 2, and Group 3 are all joined with the AND operator. Once the primary search is done, the results are manually verified to check whether some of the most well-known publications in the different fields are included in their respective lists. Next, the potential search results are assessed by considering criteria described in Table 2. Upon completing the literature retrieval process, the papers are analyzed and grouped based on the aims and approaches of this review. Table 3 summarises the search results of each related area. We understand particular papers might have been excluded from the search engine, or some unrelated papers that mention the keywords in the abstract might fall in the selection. With our manual check, we found that the number of these cases was minimal, and the trends are representative enough to draw some general analysis.

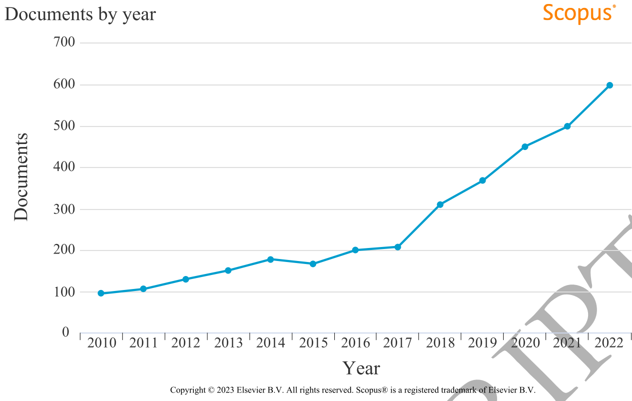


Fig. 2. AI research trend in railway infrastructures.

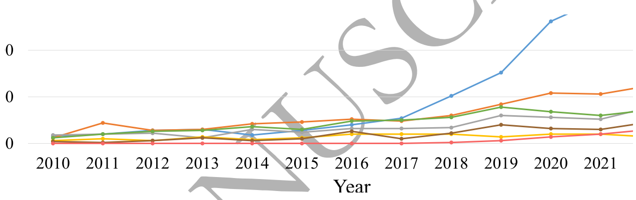


Fig. 3. Utilisation trend of each AI methodology for railway infrastructures.

2.2. Bibliographical analysis

The quantitative analysis assisted in identifying 3,465 papers. These are illustrated in Figure 2 in which an overview of research trends observed from the number of publications by year from 2010 to 2022 is given. As expected, research with AI applications in this field has gained popularity over the last twelve years. Between 2010 and 2017, the number of publications per year rose slightly from 95 papers to 208 papers. The number of publications expanded significantly after 2017. This made the overall number of publications after 2017 approximately two times greater than that between 2010-2017. This increasing trend over the past five years indicated the need and demand for AI technology developments in the railway infrastructure domain.

Next, the current progress of AI applications in rail infrastructure is overviewed based on the AI methodologies elaborated in the previous section. Figure 3 illustrates the utilization trend of each AI methodology for railway infrastructures. It can be seen that the four most commonly used methods in rail infrastructure are neural networks, metaheuristics, PGM, and regression. The total amount of publications using the neural network-based method was the biggest.

A breakdown of the relative utilization of the AI categories over the years is also shown in Figure 3. It can be seen that the utilization trend of the neural network-based method shot up in 2017. This made the neural network-based method the most deployed in 2022. For other AI categories, their utilization trend progressed similarly over the past decade. However, a slight drop was observed in the research trend using fuzzy-based methods. Note that no publications about railway infrastructure that employ transfer learning have been found before 2018. Its upsurge of interest was noticed after 2018.

An overview of the AI research share for railway infrastructure systems is presented in Figure 4. AI has been employed the most in track systems, whereas less attention has been paid

Table 1. Search terms for retrieving publications.

Group	Related area	Identified search terms
1	Railway infrastructure	rail* AND (catenary OR pantograph OR rail" OR track* OR ballast* OR weld* OR joint* OR switch* OR turnout* OR fasten* OR level crossing*" OR sleeper* OR tunnel* OR bridge* OR viaduct* OR culvert* OR subgrade* OR substructure OR soil OR embankment)
2	Railway application	monitoring OR diagnos* OR prognos* OR detect* OR predict* OR classif* OR maintenance
3	AI	computational intelligen*" OR artificial intelligen*" OR big data" OR machine learning" OR deep learning" OR computer vision" OR probabilistic* OR bayesian OR markov OR belief network" OR transfer learning" OR domain adaptation OR clustering OR k-mean OR regression OR neural network" OR convolution* OR encoder OR heuristic* OR fuzzy particle swarm" OR genetic algorithm" OR evolution*

Table 2. Inclusion criteria.

Criterion	Description
1	Only papers in track systems, catenary system, civil structures, and substructures.
2	Only papers in monitoring and maintenance.
3	Only papers that focus on using AI.
4	Papers in railway signalling, rolling stock, and operations are excluded.

Table 3. Summary of the search results.

Group	Related area	No. of papers
1 & 2	Railway infrastructure	17,393
3	AI	4,284,974
1 & 2 & 3	AI in railway infrastructure	3,465

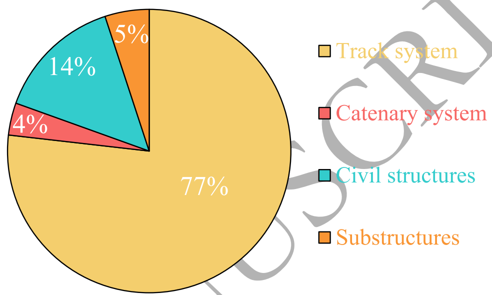


Fig. 4. An overview of the AI research share across railway infrastructure systems.

Fig. 5. The proportion of AI research papers per component. NB: one research paper can include multiple railway components.

to catenary and substructure systems. To obtain insight into the share of AI in railway infrastructure research, a comparison between the number of publications using AI and without AI is exhibited in Figure 5 per selected railway component. To retrieve the relevant AI papers per component, the associated search terms from the selected railway component from Group 1, all railway applications from Group 2, and all AI methodologies from Group 3, shown in Table 1, are all joined with the AND operator. In this figure, the analysis of viaducts and culverts is included with bridges, the analysis of substructures includes soil, and wheels are included due to wheel-rail dynamics. Even though rails, wheels, and bridges are the top three components that have received the highest attention in research, their proportion of AI research papers is less than that of catenary and pantographs. Substructures and embankments have received the least attention in research, and their proportion of AI research is also lower than the other components. Further discussions on the underlying reasons that prevent the use of AI methodologies for these components will be given later.

Figure 6 presents the distribution of AI methodologies across the four groups of railway infrastructure. Unlike the retrieval process of Figure 5, the search terms for Figure 6 were more restricted to the selected AI methodology. Without including general terms of AI, this resulted in the number difference between Figure 5 and Figure 6 due to particular papers being excluded from the search engine. However, the analysis is to draw some general trends. Based on this, some insightful findings are drawn:

1. For all four groups of railway infrastructures, neural networks, meta-heuristics, PGMs, and regressions are the most commonly used methodologies.
2. Among the four groups, neural networks dominate the catenary system with a share of 55%. The track system follows with a 34% share, while civil structures and substructures account for 27% and 22%, respectively. In contrast, transfer learning exhibits limited applicability, constituting only a 1% share in both the track system and civil structures.
3. All the selected AI methodologies have been adopted to tackle issues in railway track system and civil structures.
4. Not all the selected AI methodologies have been adopted to tackle issues in every component of the railway track system, catenary system, and substructures. There was no deployment of transfer learning in some components of the track system, the catenary system, and substructures, whereas transfer learning has been applied to civil structures. Railway welds and joints are examples that researchers have not used transfer learning for the track system.
5. Even though regression was widely used amongst other railway components, there was no publication (to the best of our knowledge) about those methods in research for

fasteners. Likewise, no research was conducted on fasteners using fuzzy logic.

6. There were limited numbers of AI methodologies applied to embankments. To the best of our knowledge, AI research was conducted using only methodologies from neural networks, metaheuristics, PGMs, and regression. There was no deployment of clustering, fuzzy logic, or transfer learning for embankments.

In Figure 7, the recent development of the selected AI methodologies in 2023 is presented across the four groups of railway infrastructure, and a summary is given as follows:

1. Within the context of the track system, railway researchers tend to focus more intently on rails, wheels, and ballasts, with comparatively less attention to welds and fastenings. Similar to the AI developments observed in the preceding years, all the selected AI methodologies have been applied within the group and the utilization of neural networks is more prevalent than those of the other methodologies. Transfer learning is the least popular method, and its applications remain absent in welds and joints in 2023.
2. Within the context of the catenary system, the utilization of transfer learning remains unexplored. A number of research is distributed equally between catenary and pantographs, using predominantly methods stemming from neural networks. As of 2023, there exists no research employing fuzzy logic within the catenary system.
3. The development trend of the selected AI methods in civil structures is similar to the catenary system. Nonetheless, all the selected AI methodologies have found their applications within civil structures. Notably, there exists research employing transfer learning in the context of bridges, but such applications have yet to extend to tunnels.
4. The recent trend of AI method development in substructures also shares similarities with that of the catenary system. Notably, the utilization of neural networks is less than metaheuristics in embankments, and employment of transfer learning is still missing.

3. AI in railway infrastructure

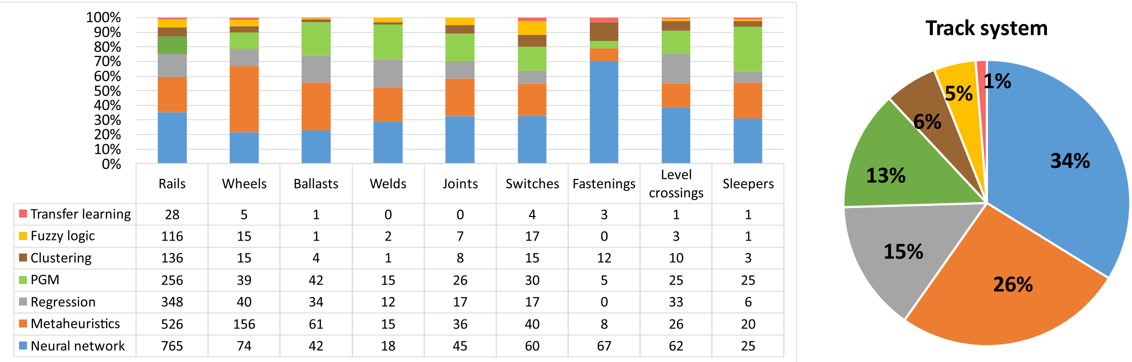
Beyond a safe railway operation, multiple aspects have to be taken into account by the inframanager and railway operators. For instance, to minimize passenger and freight delay, to maximize the capacity at which they can operate their networks, to maximize the reliability of the infrastructure, and to do all of these at minimum costs. Further, societal and environmental impacts also have to be addressed. To achieve those targets, the infrastructure needs to be reliable. This can be achieved by proper maintenance strategies that can be used for requirements of new designs when tackling root cause problems or new maintenance procedures over a lifecycle that also considers the interlinks between replacements and recycling processes. This is the so-call prescriptive maintenance. It is a new maintenance concept emerging in the railway industry along with the development of business globalization. Similar to the other maintenance concepts, prescriptive maintenance comprises information from the diagnosis and prognosis and maintenance decision-making. Its goal is also to intelligently monitor, predict, and optimize the performance of railway infrastructure. In prescriptive maintenance, component health information should represent a trend, and a major focus is on analyzing the root cause of abnormal behavior, not just the symptoms. However, the successful implementation of prescriptive maintenance in railway infrastructure requires the development of new AI solutions. This includes solutions from defect detection, root-cause identification, classification, and prediction of degradation patterns to decision-making supporting maintenance planning. Following is a narrative literature review to offer insights into the use of AI methodologies in railway infrastructure.

3.1. Railways and neural networks

Neural networks are non-linear models that can be used to capture the dynamics of complex systems. Their architecture/model structure is based on layers, namely the input layer, hidden layer, and output layer. Each layer comprises interconnected processing units (called neurons) to uncover the underlying patterns or relationships within a dataset. Neural networks can be constructed 1) with different topologies in which connections between processing units can be designed differently, 2) with different input signals in which input neurons can accept continuous or binary values, 3) with different internal state dynamics, and 4) with different learning processes to perform certain tasks. Contrary to multiple-layer neural networks, typically considered as shallow networks, deep neural networks consist of many layers commonly ranging from several tens to more than hundreds. They are designed to automatically learn and extract representations from raw input data. Deep learning, with its emphasis on deep architectures and hierarchical representation learning, has been developed and gained much attention from researchers to leverage the capabilities of neural networks for feature transformation and extraction in big data environments. Examples of neural networks are multilayer perceptron, artificial neural network, spiking neural network, graph neural network, radial basis function network, residual neural network, convolution neural network, and recurrent neural network. Interested readers in the field of neural networks are referred to review papers such as (124; 5), and recent reviews such as (1; 139; 52).

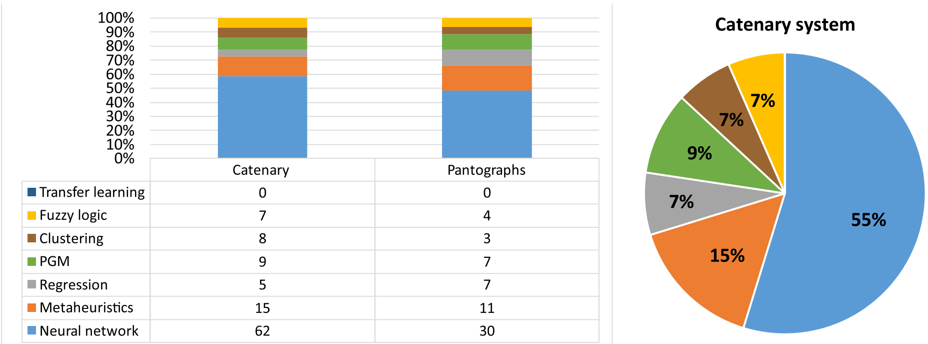
Much of modern technology is based on big data environments with highly inherent complex relationships between dependent and independent variables. In railway infrastructure, both neural networks and deep neural networks have found their applications for various railway infrastructure components, e.g., rails (61), catenary (64; 21; 162), tracks (44; 106; 159; 50; 41), fasteners (21; 159), tunnels (4), turnouts (39), and bridges (128). The existing applications of neural networks focus, among others, on detection (61; 64; 21; 162; 44; 106; 159; 128; 71), prediction (50; 41; 4; 39), and decision-making (61; 106). In the railway industry, there have been various applications of neural networks and deep learning to detect defects and anomalies and to diagnose and prognose of railway infrastructures including rails, level crossings, switches, welds, catenary and pantographs.

In the research topic of detection, the challenge is to achieve complete automation of defect detection at the early stages (64; 162; 44; 128). Algorithms based on deep convolutional neural networks (DCNNs) are predominantly utilized in railway fault inspection and detection (61; 64; 21; 162; 44; 106). This is due to the capabilities of DCNNs and the popularity of vision-based inspection. Dealing with vision-based data, intensive research has been devoted to alleviating problems concerning image quality acquired from inspection systems (64; 21; 44; 159; 71).



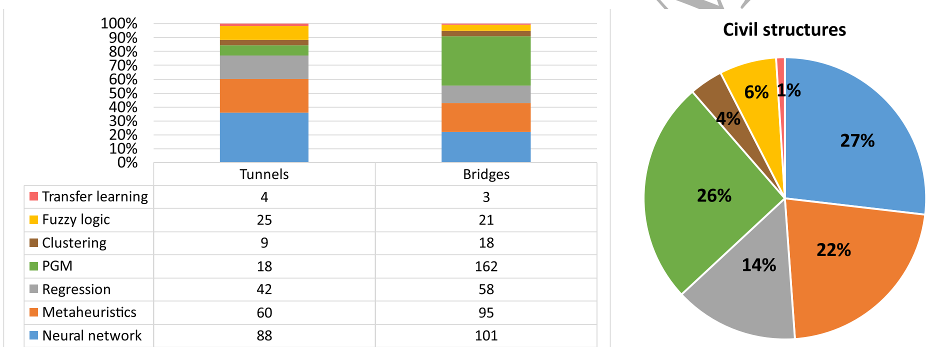
	Rails	Wheels	Ballasts	Welds	Joints	Switches	Fastenings	Level crossings	Sleepers
Transfer learning	28	5	1	0	0	4	3	1	1
Fuzzy logic	116	15	1	2	7	17	0	3	1
Clustering	136	15	4	1	8	15	12	10	3
PGM	256	39	42	15	26	30	5	25	25
Regression	348	40	34	12	17	17	0	33	6
Metaheuristics	526	156	61	15	36	40	8	26	20
Neural network	765	74	42	18	45	60	67	62	25

(a) Across track system.



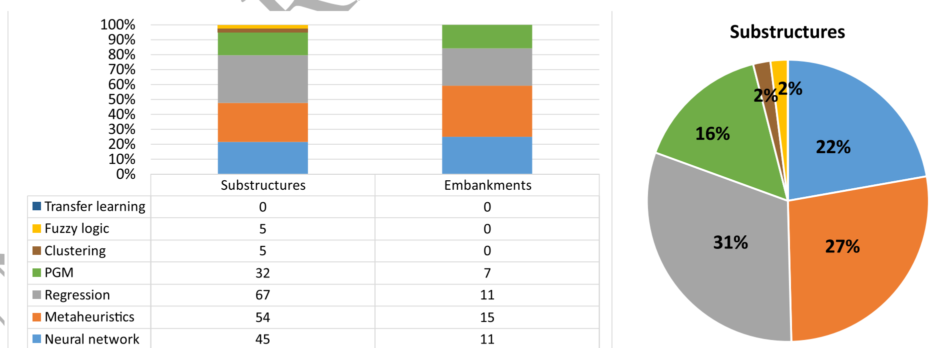
	Catenary	Pantographs
Transfer learning	0	0
Fuzzy logic	7	4
Clustering	8	3
PGM	9	7
Regression	5	7
Metaheuristics	15	11
Neural network	62	30

(b) Across catenary system.



	Tunnels	Bridges
Transfer learning	4	3
Fuzzy logic	25	21
Clustering	9	18
PGM	18	162
Regression	42	58
Metaheuristics	60	95
Neural network	88	101

(c) Across civil structures.



	Substructures	Embankments
Transfer learning	0	0
Fuzzy logic	5	0
Clustering	5	0
PGM	32	7
Regression	67	11
Metaheuristics	54	15
Neural network	45	11

(d) Across substructure system.

Fig. 6. Distribution of the selected AI methodologies across the four groups of railway infrastructures. NB: one research paper can include multiple AI methodologies.

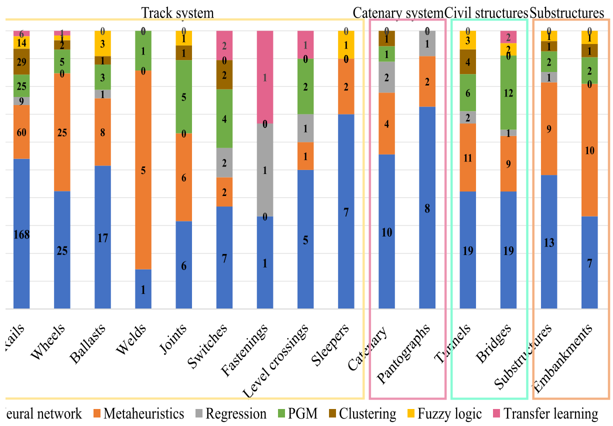


Fig. 7. Development of the selected AI methodologies in 2023.

To deal with the visual complexity of defects and the similarity between the component and background, Kang et al. (64) and Chen et al. (21) proposed methodologies based on DCNNs. Many modules were considered in developing the detection system, including component localization and defect detection. In the component localization module, object detection algorithms employed were the single shot multibox detector, You-Only-Look-Once, a region convolutional neural network (R-CNN), and fast R-CNN. Besides a fully convolutional Network used in (21), a deep multitask neural network integrating both a deep material classifier and a deep denoising autoencoder into its architecture was introduced in (64) to accomplish simultaneous segmentation and defect detection. To obtain better high-speed performance in detection, Zhang et al. (159) proposed a novel structured light method based on motion image to assist a feed-forward neural network for an inspection of moving objects.

For prediction, neural networks are mainly selected due to their universal approximation capabilities for non-linear systems, self-adaptation, and the precision of their predictions. Some of the algorithms utilized within the area of railway prediction are neural networks trained with back-propagation (50), multi-layer perceptrons (41; 4), multi-valued neural network (39), and several other algorithms. Multilayer feedforward neural networks based on multi-valued neurons (MLMVN) proposed by Fink et al. (39) were applied to predict reliability and degradation based on time series. This research demonstrated that the MLMVN developed good results for multi-step ahead predictions and did not show accumulating errors.

Jamshidi et al. (61) and Oukhellou et al. (106) presented a framework using a neural network to detect faults. A data-fusion technique based on Bayesian probability theory was considered afterward to combine the outputs from a neural network in order to make a final decision on the detection and localization of a fault in the system. The DempsterShafer theory was considered in (106) while Bayesian inference was considered in (61). The DempsterShafer theory provides a convenient framework for handling imprecision and uncertainty in decision problems regarding the presence and location of a fault.

3.2. Railways and regression

Regression and AI typically build models based on a labeled set of data examples and predict a certain data characteristic. For instance, the regression models can be used to evaluate new data, which will tend to provide a prediction as the examples provided in the database. A new data point with a high similarity measure to a data point in the dataset indicates the best match to predict a certain output (54). Examples of regression algorithms are logistic regression, ridge regression, linear regression, stepwise regression, ordinary least-square regression, multivariate adaptive regression, principal component regression, partial least-square regression, and project pursuit regression. For recent review papers on regression, readers are referred to (99; 131). Regression has been widely employed in rail infrastructure due to its simplicity. Based on our review, regression has been used for association, prediction, and assessment.

For association, examples of algorithms are Bayesian regression (147), logistic regression (29), auto-associative kernel regression (20), locally weighted regression (20), partial least squared regression (136), etc. Chen et al. (20) employed an auto-associative kernel regression to explicit mapping relationships between the remaining useful life and health indexes to provide a reliable and effective RUL estimation. Sysyn et al. (136) employed principal component analysis and partial least squares regression to show a significant statistical relationship between a change in the dynamic response of a railway crossing and the rolling surface degradation during the life cycle of the crossing.

For prediction, Wang et al. (147) employed Bayesian regression, a generalized linear regression method, for probabilistic assessment of crack-alike rail damage using acoustic emission monitoring data. This was developed based on a nonparametric approach in the context of Bayesian inference with the combined use of Bayesian regression and Bayes factor. To forecast the degradation of track geometry, Cardenas-Gallo et al. (29) proposed an ensemble classifier based on deterioration, regression, and classification. In regression, a binary logistic regression model was employed to predict how the future state of a particular defect is described by the independent variables.

Regression-based methods have also found their applications in feature extraction and selection in railway infrastructure. A multivariate regression analysis with feature selection and extraction techniques contains many popular methods like stepwise regression, ridge and lasso regression, principal components analysis (136), partial least squares regression (136), proper orthogonal decomposition (36), and locally weighted regression (20), etc. Azam et al. (36) developed a framework to detect damage under operational conditions in railway truss bridges. Before using an ANN to detect damage, the proper orthogonal decomposition was employed to categorize responses to different load patterns of trains near a bridge in their work. In (136), principal components analysis and partial least squares regression were two feature extraction methods applied to determine the rolling surface degradation during the life cycle of a crossing. To reduce the noise interference, the extracted features and the combined health indicators are all smoothed using the locally weighted regression in (20).

3.3. Railways and metaheuristics

Metaheuristics are strategies that guide the search for near-optimal solutions to an optimization problem. Convergence to a global optimum is not guaranteed, yet statistical analysis shows that these techniques can systematically get close to a global optimum. Their performance is rather problem-specific, but their fundamentals can be applied to a broader class of problems. Their search techniques range from local-search to global-search-based procedures, such as population-based approaches. Examples of metaheuristic algorithms are differential evolution, evolutionary computation, particle swarm optimization (PSO), genetic algorithms (GA), and ant colony optimization. For recent review papers on metaheuristics, readers are referred to (154; 155; 53).

In recent years, metaheuristics have been applied to various railway infrastructures, e.g., welds (104), bridges (142; 125; 120; 115; 28), tracks (161; 127), rails (16; 27; 110; 78), catenary and pantograph (74; 122). According to our survey, applications of metaheuristics lie within model updating (142; 120; 115; 28; 127) and optimization in structural design (125; 27; 110; 78; 74), maintenance (104; 159; 16; 47), and operations and control (122).

In structural health monitoring and safety assessments, the Finite Element Method (FEM) is the standard tool for modeling the structural behavior of railway infrastructures. However, the FEM cannot accurately represent the dynamic characteristics of a structure due to a wide range of simplifying assumptions. To achieve a more suitable finite element model of the structure (120; 28; 129), calibration, a.k.a. model updating, on uncertain parameters in the model with new measurements is typically needed. This aims at minimizing the relative difference between analytical predictions and experimental measurements. GA and PSO are two optimization techniques widely used for this purpose. GA is a search and optimization technique inspired by the process of natural selection and genetics. PSO, on the other hand, is inspired by the collective behavior of bird flocking or fish schooling, where particles adjust their position based on their own experience and the experience of their neighboring particles. With its simplicity and trustworthy evaluations, GA has been used in (142; 120; 28) to enhance assessment performance. In (142), Tran-Ngoc et al. employed GA to update the unknown model parameters for a railway bridge. Costa et al. (28) proposed an iterative method based on GA to minimize the differences between numerical and experimental modal responses of a stone masonry arch railway bridge. Ribeiro et al. (120) described the finite element model updating of a bowstring-arch railway bridge based on experimental modal data using an iterative procedure with GA.

As GA usually takes more time to converge towards a global optimum, PSO has been employed by researchers to find the global optima of the problem. Qin et al. (115) applied the kriging model and PSO for the dynamic model updating of bridge structures using the higher vibration modes under large-amplitude initial conditions. Tran-Ngoc et al. (142) employed PSO to minimize the discrepancies between the experimental and the numerical results. A comparison between applying PSO and GA was also studied in their work. The results showed that the PSO algorithm provided better accuracy, and it reduced the computational time compared to GA. For model updating, Shen et al. (127) employed PSO and proposed a fusion strategy that directly infers the stiffness of the rail pad and the ballast from measured frequency response functions based on Gaussian process regression. It was demonstrated that their fusion method outperformed the PSO method in terms of accuracy and time efficiency.

Metaheuristics have also been applied for structural design optimization. GA is the most widely used technique within this area based on our literature search results. Sgambi et al. (125) proposed a method based on the combined application of GA and FEM to design a complex long-span suspension bridge. In (110), GA was used to optimize the rail profile on the Stockholm underground to alleviate a problem with rolling contact fatigue without consequent issues with wear and noise. Li et al. (78) proposed a hybrid method to design a challenging railway alignment for topographically complex mountainous regions. The hybrid approach uses a bidirectional distance transform and GA. Even though this hybrid method improved the performance of GA and solved the challenging problems concerning topographically complex mountainous regions, it was computationally more expensive than the other existing methods. In addition, differential evolution is another technique used in (74; 19). In (74), differential evolution was used to define the regressive function and to determine the optimum values for stable current collection performance of the pantograph for a high-speed train. In (19), the railway track Health monitoring system employed a dynamic differential evolution algorithm for identifying defects in railway tracks. In (13), Harris hawks optimization with PSO-based mutation were used for predicting soil consolidation parameter. In (31), the performance of the Grey Wolf optimization, PSO, and GA were compared for the estimation of railway track parameters. Their results showed that the Grey Wolf optimization performed the best in most of the used tested cases.

The information provided by the metaheuristic-based methodology can be used to support the decision for maintenance. Typically, most optimization solutions in railway infrastructures have focused on single-objective problems. To schedule the maintenance crew for freight rail optimally, Gorman et al. (47) adopted three techniques (mixed integer programming, constraint programming, and GA) and compared them. The results showed that the mixed integer programming network formulation showed the most potential for quickly finding quality solutions among the techniques used. Zhang et al. (161) developed an enhanced GA approach to deduce the optimal scheduling for the maintenance work of railway tracks in the UK. In the enhanced GA, they employed various additional techniques, e.g., orthogonal experimental design to initialize the population, roulette selection to generate a population for the next generation of solutions, and the differential evolution operator to perform the variation process. Moreover, the selection was executed on the pooled solutions from both the parent and the newly generated offspring to guarantee that the best solution was not disregarded.

However, in railway maintenance optimization, focusing on a single objective is not always valid. In the structural health monitoring context, sometimes two or more failures often occur simultaneously. It is thus necessary to consider all related goals as bi-or multi-objective functions to be optimized. These objectives make it challenging to find a single solution that optimally satisfies all of them simultaneously. Evolutionary Multiobjective Optimization (EMO) is a computational optimization technique that aims to solve problems with multiple objectives.

In the maintenance context, reliability, life-cycle costs, and sometimes environmental costs are to be considered. Such optimization concerns multiple objectives and searches for solutions in the global Pareto-optimal region, where solutions cannot be reallocated to make one objective better off without making at least one of the others worse off. This is to achieve solutions that are separated from one another to the maximum possible extent to form the trade-off surface in the objective space (16). Various multi-objective methods have been employed to obtain multiple Pareto optimal solutions. Generally, two classes can be distinguished: genetic algorithm-based

(104; 16; 27; 122) and evolutionary algorithm-based approach (104). In (104; 16; 27; 122), multi-objective optimization was handled by a fast nondominated sorting genetic algorithm (NSGA). In (122), NSGA2 was used to optimize both the contact force and the consumption of the energy supplied by the control force for the design process and control of the catenarypantograph system. In (27), Choi et al. adopted NSGA2 to minimize both the wear and fatigue of a wheel with consideration for derailment, lateral force, vehicle overturning, and vertical force generated during motion along a curved track. The research objectives of Caetano (16) was to support an informed decision that considered not only the railway track life-cycle cost but also the track occupation. Nunez et al. (104) also performed multi-objective optimization to identify the set of all Pareto optimal solutions that formed the trade-off surface between performance and maintenance cost for rail welds in a regional railway network. In their work, a multi-objective optimization tool from Matlab was used, and the algorithms ARMOEA, NSGA2, SPEA2, GrEA, RSEA, and VaEA, were compared. It was shown that SPEA demonstrated superiority among other algorithms for their proposed maintenance decisions optimization problem, at least when the number of integer decision variables was not extremely large.

3.4. Research based on probabilistic graphical model

A probabilistic graphical model (PGM) expresses relationships between variables based on graphic architectures. It operates to provide an intuitive framework for representing uncertainty using probability distributions (143). PGMs can be divided into two classes, i.e., Bayesian models and Markov models (75). Examples of algorithms within PGMs are Nave and non-Nave Bayesian, Bayesian (belief) network, Hidden Markov model, Markov models, and Averaged one-dependence estimator. For recent review papers on PGMs, readers are referred to (95; 126).

PGMs have been applied for various railway infrastructures, e.g., railway bridges (118; 46; 103), catenary (86), turnouts (145; 34), rails (60), tracks (6). They are considered a powerful tool for anomaly quantification in the presence of uncertainty. There has been a growing interest in applying PGMs to fault diagnosis and prognosis in railway systems. In particular, they offer solutions to damage detection, predicting the future conditions of railway infrastructures, identifying causality inference, and providing a learning mechanism that can be adaptive over time.

For railway infrastructures, it happens that multiple failure events cannot be identified and the probability of failure cannot be reached quantitatively by event tree and fault tree analysis (34). Many researchers have then proposed methods based on the Bayesian network to identify the probability and the underlying root cause of failures in railway infrastructures through various basic principles and inference algorithms. Generally, the systematic Bayesian networks are developed in three steps; 1) variable selection, 2) structural design of the Bayesian network, and 3) parameter learning. Wang et al. (145) proposed a Bayesian network for weather-related failure prediction in railway turnout. In the Bayesian network development, they first selected variables that related to weather and failures. An entropy minimization-based method was presented to discretize model variables in order to reduce the input type and to capture better performance. In the second step, they designed the structure of the Bayesian network by learning from real data combined with expert experience. Lastly, in parameter learning, the Bayesian network was transferred into a noisy independence of causal influence model and took advantage of learning the conditional probabilities using a noisy MAX model to overcome the parameter learning problem from small data sets. Monte Carlo simulations were also employed to determine with greater accuracy the mean and the confidence interval for weekly estimations of failures. Dindar et al. (34) employed a Bayesian network to analyze the probability of train derailments caused by extreme weather patterns on railway turnouts. They followed the same steps as in (145) but employed fuzzy probability using Buckleys confidence interval-based method to allow for gathering more information than just a single confidence interval or just a point estimate in the last step of the Bayesian network development. As opposed to (145; 34), Imran Rafiq et al. (118) proposed a dynamic Bayesian network to model the variation in the bridge condition with time. In a dynamic Bayesian network, the Bayesian model is connected to its successive time slices through temporal links to form a time-varying model, while the Bayesian network model discussed in (145; 34) serves as a snapshot model to estimate the railway infrastructure condition based on its constituent element conditions at a given point in time. Markov chain principles were employed to quantify the transitional probabilities in (118).

PGMs are computationally efficient in updating the model when new information regarding the condition state of any variable becomes available. Neves et al. (103) proposed a PGM-based method to update an ANN model for damage detection of railway bridges. In their work, a Gaussian process was employed to statistically analyze the distribution of the errors using the predicted acceleration errors obtained from the developed ANN. This was to define the detection threshold for the system, allowing the determination of the probability of true and false detection events. Finally, probability-based expected cost, as a function of the chosen threshold, was proposed based on the theorem of Bayes to update the model. To infer some stiffness properties of the ballast and subsoil from measurements carried out on the railway bridge, considering uncertain seasonal effects, Gonzales et al. (46) also employed Bayesian updating of a 3D finite element model with Markov-Chain Monte Carlo sampling to determine posterior distributions of the uncertain stiffness properties in the warm and cold states of the bridge.

Another typical application of PGMs is for analysis of the risk factors correlated with failures in railway systems. Jamshidi et al. (60) proposed a failure risk assessment framework based on the PGM for analyzing the rail surface defects called squats. The proposed framework aimed to estimate the probability of rail failure based on the growth and severity of rail squats. In their work, defect severity and growth analysis were performed via an N-step ahead prediction model using data measured by ultrasonic detection. To assess model uncertainty and robustness for stochastic data behaviors, the Bayesian inference model was employed to estimate the failure probability. Andrade et al. (6) used a hierarchical Bayesian model to handle the spatial correlations of the deterioration rates and the initial qualities for consecutive track sections. With a hierarchical Bayesian model, the predictive model for the degradation of railway track geometry was improved based on the deviance information criterion.

Furthermore, a Markov random field model was developed in (86) for image segmentation in order to facilitate automatic fault detection for the loose strands of the isoelectric line in the catenary system. This work employed the Markov random field model to provide a link between the uncertainty description and prior knowledge in their work. They showed that detection accuracy was improved with the use of Markov random field.

3.5. Railways and fuzzy systems

Fuzzy logic can deal with ambiguity. While traditional logic allows a proposition to be either true or false, in fuzzy logic, a proposition has a degree of truth, ranging from being completely true to completely false. A formulation based on fuzzy logic is defined by multi-valued logic where the value of a variable can be any real number between, but not limited to, 0 and 1. The applications of fuzzy logic-based methodology often lie within solving a problem with uncertainties, vagueness, or imprecision (143). Examples of fuzzy logic methods are type1- type2-fuzzy logic, Takagi-Sugeno fuzzy inference system, Mamdani fuzzy inference system, fuzzy C-means, and adaptive network-based fuzzy inference system. Interested readers in fuzzy logic are referred to review papers such as (96; 132; 33; 72).

The applications of fuzzy logic-based methods often lie within the problem of prediction and decision under uncertainties or vagueness. Examples of their applications for railway infrastructures are detection, risk assessment, and decision support (42; 62; 97; 58; 77).

For detection problems within a railway environment, false alarms are one of the biggest issues that create financial losses in the railway industry (42). False alarms are generated when the system detects a non-existent obstacle or does not detect an existent obstacle. Techniques utilized to alleviate the problem include, e.g., the design of the sensor used, the conditions in which the sensor is working, and the signal processing that is carried out by the system, Garcia et al. (42) employed a Mamdani fuzzy controller to weigh the certainty of the existence of objects given by a multisensory system to inform the monitoring system about the existence of obstacles. Hussain et al. (58) also employed a fuzzy logic-based method to deal with such uncertain circumstances in detecting adhesion and its changes under different wheel-rail contact conditions.

As detection and diagnosis systems can facilitate the decision-making process, much attention has been paid to improving the reliability of such systems by using fuzzy logic-based methods. As numerous circumstances threaten safety and operations in railway infrastructures, it is necessary to consider key performance indicators (KPIs) affecting the health conditions of railway infrastructures over time. Under the stochasticity of operational conditions, fuzzy logic-based methods have been adopted to assess the dynamics of threats. Within this context, Jamshidi et al. (62) and Li et al. (77) proposed a technique stemming from fuzzy logic. To assess the dynamic of water inrush in the progressive process of tunnel construction, Li et al. (77) employed a fuzzy evaluation method to quantitatively analyze the risk level of factors concerning both geological condition and construction situation. Jamshidi et al. (62) presented a fuzzy TakagiSugeno interval model to predict squat growth over time under different possible scenarios and under different maintenance decisions. Moreover, a Mamdani fuzzy expert system was used to calculate a single KPI to conclude the dynamics of the deterioration of railway tracks.

In addition to railway safety and operations, there are increasing requirements concerning riding comfort. As railway tracks deteriorate over time and maintenance becomes expensive, Metin et al. (97) presented a fuzzy logic controller to ensure that the vibration responses are within permissible limits. In their work, the performance of the fuzzy logic controller was compared with the conventional proportional integral derivative controller. The results showed that the fuzzy logic controller demonstrated superiority in active vibration control and increased passenger comfort. Other notable AI techniques applied in catenary systems using fuzzy logic are (156; 67; 66; 10; 11).

3.6. Railways and clustering

Clustering is a technique for partitioning a set of objects into different data groups. The procedure is done so that objects in the same cluster are more similar than those in other clusters. Further, different clusters are preferred to contain rather different samples. Thus, clustering methods require selecting an appropriate measure and an objective function that minimizes the within-cluster variation and maximizes the between-cluster variation. Different measures result in different clusters. Examples of clustering algorithms are k-means, k-nearest neighbor, self-organizing maps, mixture of Gaussian models, and hierarchical clustering. Interested readers in the field of clustering are referred to review papers such as (152; 94; 116).

Various applications in the area of railway monitoring and maintenance have been found using clustering methodologies. For monitoring, clustering can be employed to detect and assess damage in railway infrastructures. Cardoso et al. (17) proposed a clustering technique to uncover hidden patterns in monitoring data. A hierarchical clustering algorithm was applied to modal parameters and used to perform automated modal identification in railway bridges. Unlike (17), Cury et al. (30) proposed a novel technique based on symbolic data analysis for providing a clustering of different structural states in which the number of states is not known a priori and has to be determined. The symbolic clustering methods considered in (30) included hierarchy-divisive methods, dynamic clustering, and hierarchy-agglomerative schemes. The results highlighted the large capability of the symbolic data analysis methods to provide clusters of different structural behaviors in railway bridges. Both hierarchy-divisive and dynamic cloud methods demonstrated better results compared to those obtained by using the hierarchy-agglomerative method.

Clustering-based methodologies have been applied to support decisions for the optimal planning of maintenance of railway infrastructures. Within this context, Cirovic et al. (59), Su et al (133), and Peng and Ouyang (108) presented a clustering technique to determine groups of maintenance jobs and groups of railway assets that can be treated within either the allocated time slots or budget allowance. In (59), Cirovic et al. proposed a technique based on fuzzy clustering to define the optimal strategy which supports the choice of level crossings for installing safety equipment in Serbian railway. These criteria were used to form a set of data for training the adaptive neuro-fuzzy network. In (133), Su et al. solved a mixed integer linear programming problem to obtain the resulting optimal clusters of railway components that were treated within the allocated maintenance time slots. This was to determine the trade-off between traffic disruption and the total setup cost associated with each maintenance slot while guaranteeing that the total duration of the resulting maintenance slots was no less than the estimated maintenance time. In (108), F. Peng and Y. Ouyang also employed a mixed-integer mathematical programming model in the form of a vehicle routing problem with side constraints to classify track maintenance jobs into projects. The algorithm framework of job clustering considered in their work included a constructive greedy heuristic, a local search heuristic, and a feasibility heuristic.

3.7. Railways and transfer learning

Transfer learning-based methods are developed to tackle problems concerning limited labeled data in supervised learning. The knowledge from one or multiple tasks (the source domain) is expected to transfer to other related but different ones (the target domain). The transfer scenarios can be divided into two categories, i.e., transfer in the identical machine and transfer across different machines (75). The latter is also known as domain adaptation, where differences between feature spaces and label spaces are allowed, e.g., transferring knowledge from railway track to railway catenary. For recent review papers on transfer learning, readers are referred to (166; 70).

The existing supervised AI learning algorithms manifest a relatively advanced performance in different railway engineering applications. Their fruitful performance relies extensively on sufficient training data and high-dimensional balanced datasets (64; 44; 106). Otherwise, imbalance and insufficient labeled datasets can impair the ability of, e.g., the classification algorithms. For railway engineering, the amount of monitoring data collected from railway infrastructures, especially defective samples, cannot generally be collected in a short time to obtain balanced datasets for network training under different operating conditions (164; 25; 153; 167). To alleviate this issue, increasing attention has been paid to developing algorithms based on the transfer learning approach. It refers to the concept of transferring the knowledge of the pre-trained model to other related but different ones. The transfer scenarios can be developed using other AI methodologies such as CNN (164; 25), deep learning (153; 167), and AdaBoost (164; 80).

Zhong et al. (164) and Chen et al (25) proposed a transfer learning approach based on CNN. In (25), a multi-layer CNN was employed in which the low-level layers of a model were pre-trained on large audio data for feature extraction. Next, the acoustic-specific features were transferred to train the high-level layers by using acoustic emission monitoring data for condition assessment of the rail structure. To overcome the problem of a limited amount of defective data, Zhong et al. (164) proposed an improved algorithm based on the Faster R-CNN algorithm to build a transfer learning model in defect localization.

Based on deep learning, Zhong et al. (164) also introduced an algorithm based on a generative adversarial network to construct defect detection models by using only normal samples. Yao et al. (153) employed a generative adversarial network to generate additional fault samples in order to balance and train the data sets. Residual Network was developed for fault diagnosis and classification of track fasteners, and the extended data set was used for group training and validation. With generative adversarial network and residual network, the results showed that the fault detection accuracy of rail fasteners did not impair when using a serious shortage of fault data. In (167), Zhuang et al. employed firstly extended Haar-like features to extract effective features of cracks on railway ties and fasteners. Secondly, a cascading classifier ensemble was developed by integrating individual cascading classifiers built via the LogitBoost algorithm with a bootstrap aggregation. However, the framework proposed in (167) could not identify patterns that were not included in the training dataset.

Among transfer learning algorithms, the Adaboost algorithm is one of the most widely used tools to overcome the problem of insufficient training data. The core idea of AdaBoost is to iteratively train the weak learning algorithm, whose predictive performance is lower, for the same data set and integrate them into a strong learning algorithm, whose predictive performance is higher. Lin et al. (80) employed AdaBoost to relate catenary fault frequency with meteorological conditions. In their work, only a small number of training samples were classified correctly by each weak classifier chosen from the single decision tree. The AdaBoost algorithm was adopted to adjust the weights of misclassified samples and weak classifiers and train multiple weak classifiers. Finally, the weak classifiers were combined to construct a strong classifier for the final prediction.

Transfer learning can be applied to a pre-trained model of any type and transfer learning alone particularly deals with the issue when the amount of available data for the target task is limited. However, the combination of transfer learning with other neural network architectures (such as recurrent neural networks, and convolutional neural networks) can lead to hybrid models that leverage the strengths of different approaches, providing more accurate solutions for railway problems. Furthermore, when multiple neural networks are trained independently, the knowledge of the pre-trained models can be aggregated by using transfer learning in an ensemble setting and can be adapted to different railway networks or different environments. The combination of transfer learning with neural networks can potentially lead to improved performance, generalization, and robustness. In (22), the concept of transfer learning was applied to deep convolutional neural networks for multi-category damage image classification recognition of high-speed rail reinforced concrete bridges. The results showed that the approach reduced the training time of the neural network models and led to lower generalization errors. In (158), deep transfer learning and graph neural networks were proposed for the health assessment of high-speed rail suspension systems. Using transfer learning in an ensemble setting to combine transferable features in the source domain, the shortage problem of labeled data in the real operating condition was alleviated as the initial hyper-parameters of the model in the target domain were obtained from the pre-train model in the source domain.

3.8. Discussion

Table 4 presents the potentials of the selected AI methodologies for applications in railway infrastructure and their limitations. Based on these, some insightful findings are:

- Neural networks require further adaptations to describe real-world physical interpretation due to their black-box characteristic. Having a black box model that is not guaranteed to perform under new unexpected conditions makes the users and rail operators concerned about the use of the model predictions. Based on the review in this section, it is observed that several works have applied neural networks in combination with regression (4; 128) and other soft-computing techniques, e.g., support vector machine (71), decision tree (106), and fuzzy (61) to provide more explainability about the correlation between model behaviors and the physical problem.
- It was observed that researchers have developed hybrid models combining two (or more) AI techniques to perform a specific task. Examples of combing AI methods are 1) meta-heuristics-based method with neural network-based method (78; 103), 2) PGM-based method with neural network-based method (61; 106), 3) regression-based method with PGM-based methods (147; 29), etc. The use of a combination of methods has the potential to improve overall performance when these methods are complementary to each other.

Table 4. Summary of potentials and limitations of selective AI methodologies.

AI methods	Tasks	Achievements	Limitations	Papers discussed in this work
Neural network	detection, association, prediction, decision support	capability to deal with non-linear and complex relationships between dependent and independent variables with high precision of the predictions	long training process to determine the optimal network and lack of interpretability	(61; 64; 21) (162; 44; 106) (159; 50; 41) (4; 39; 128) (71)
Regression	association, prediction, assessment	ability to provide an explicit mapping relationships between variables with physical meaning	non-competitive accuracy compare to other AI methods	(147; 29; 20) (136; 36)
Meta-heuristic	FE model updating, design optimization, and maintenance optimization	ability to provide optimal solution to problems concerning either single or multiple objectives.	long computation time to find optimal solution	(104; 142; 125) (120; 115; 28) (161; 127; 16) (27; 110; 78) (74; 122; 47) (13; 19; 31)
PGM	detection, prediction, identify causality inference	powerful tool for dealing with situation in the presence of uncertainty, and solving inference problems	rely on a high-quality training dataset and often suffer from the curse of dimensionality.	(118; 46; 103) (86; 145; 34) (60; 6)
Fuzzy logic	detection, assessment, control	ability to produce fuzzy rules for problems with uncertainty	highly dependent on human knowledge and expertise, and have to regularly update the rules.	(42; 62; 97) (58; 77)
Clustering	detection, assessment,	ability to discover hidden patterns in datasets without providing labelled data	inability to perform if there exists a mixture of clusters with different characteristics	(133; 17; 30) (59; 108)
Transfer learning	detection, prediction	capability to deal with imbalance and insufficient labeled datasets	inability to deal with situations when health information are unrelated.	(164; 25; 153) (167; 80)

For instance, global optimization approaches can potentially find parameters of neural networks that better fit an objective function. However, when different methods solve a similar task, a major emphasis on the analysis of the consensus between these methods is needed.

- Deep learning concerns multiple layers of computational units in which the actual optimization of the whole structure is a highly non-convex problem. They contain a huge amount of parameters and, in some cases, more than millions of parameters which results in long computation time to find a near-optimal solution. Moreover, large labeled datasets, preferably balanced, are required to train deep learning models. Despite these shortcomings, interest in these methods has increased in view of the rather impressive results from other fields. To alleviate the issues and make its advantages more pronounced, transfer learning is employed to help retrain the trained deep learning models to perform a similar task. This not only reduces computational effort but also the amount of training data for deep learning.
- PGMs and fuzzy logic have received a growing interest for applications in fault prognosis due to their powerful capability to deal with the presence of vagueness, uncertainty and solving inference problems (118; 145; 34; 60; 6). However, there are several sources of uncertainty, e.g., measurement data, model structure and parameters, and different data behavior from future operational conditions. These uncertainties propagate over time and the existing models have to be updated when new information regarding the health condition of any variable becomes available. Most existing models are computationally inefficient in updating. Based on our review, however, limited work has been found to address such a problem for railway infrastructure.

4. Challenges from railway infrastructure

State-of-the-art intelligent solutions show good generalization capabilities to solve problems from different fields. Some particular challenges from railway infrastructures prevent direct exploitation of the existing state-of-the-art methodologies, as will be highlighted in a sequel. Consequently, their successful application in the field of railway infrastructure requires designing and developing methodologies to capture the particular and challenging characteristics of railway infrastructure.

4.1. Insufficient and imbalanced data for model training

For railway infrastructure, conventional supervised methods, particularly deep learning, require a large amount of labeled data available for learning to guarantee their performance. However, collecting accurate and verified labeled samples of high-quality faulty and healthy states from thousands of km of rail lines is extremely difficult, costly, and time-consuming. Regarding class information for defects, often few labeled data are available due to the lack of historical data with sufficient quality and localization. Likewise, healthy data are difficult to label because of their variants of behavior at different locations; in particular, rails are affected by local track dynamics and different stochastic variables. Sometimes, there is no standard/threshold to evaluate the level of health conditions. For instance, an embankment is one of the areas in railway infrastructure that require further study. Furthermore, in some railway infrastructure, obtaining a wide variety of class information for defects is extremely difficult. Therefore, data from healthy infrastructure are abundant, whereas defective ones are few. As a result, the data used for training AI models are seriously imbalanced, and labeled data are insufficient.

4.2. Training AI models with complex railway data

Railway infrastructures are complex and highly nonlinear. They involve different assets and can be affected by various anomalies. Detecting failures and maintaining the structure requires multiple measurement systems. Most of the information about the condition of the infrastructure is collected with inspection systems. Typical systems in the industry include eddy current, ultra-sonic, vibration measurements between wheel and rail using accelerometers, video images and track geometry recording vehicles (135; 134). Depending on track tonnage, the number of trains passing by the track, and maximum line speed, data measurement frequencies and data processing requirements can differ substantially. Thus, selecting a proper AI methodology must account for the nature of the railway components and their inherent dynamics. There is a significant interdependency between railway track-related assets, not only in functionality but also in using anomaly detection algorithms or maintenance planning. For example, a track video scan (56; 165; 105; 111) allows the asset manager to capture the health condition of different track components, e.g., fasteners, switches, and sleepers (32; 48; 121; 137; 40; 130). However, video image-based measurements can only capture anomalies in the track structure when they are visible. This means that early-stage anomalies in rail (invisible ones) or vertical irregularities in the track cannot be detected effectively using only video cameras. Using together images and other sources of data, such as axle box acceleration (ABA) measurements, track geometry, or eddy current and ultrasonics, can provide a more integrated assessment of the track condition. ABA measurements can detect light squats (Phusakulkajorn et al.; 113), which occur at frequency bands up to 2.5 kHz with train speeds of about 100 kilometers per hour (102). New technologies, such as a Laser Doppler Vibrometer sensor, can also provide continuous monitoring along a railway line, and they can measure with frequency sampling that goes higher than the order of MHz. Thus, continuous monitoring of hundreds of kilometers with the latest technologies creates a better overview of the current track condition, but at the expense of creating a huge volume of data and a very high dimensionally problem from which key features are to be extracted to represent the data effectively. In this case, developing ultra-fast AI solutions, also considering edge computing (23), could support addressing these challenges.

In addition to the characteristics of the railway infrastructure, the most suitable AI method can be determined based on the nature of the measurement data. Measuring data can vary from an unorganized and semi-organized data structure to a fully organized structure. Measured data collected by human operators, e.g., track information and historical operational activities, usually are fully structured or semi-structured. On the contrary, advanced anomaly detection systems contain a massive sampling pool and high complexity as they are high-dimensional and nonlinear that require additional methodologies for preprocessing, including noise removal, feature extraction, and selection.

Employing multiple systems to monitor railway infrastructure performance indicates the need to deal with heterogeneous data. The information about defects obtained by a single source can easily show trends; however, it is limited by the nature of the measurement itself. When different data types are exploited to extract information and to provide additional information about the same defect, we have the risk that the data sources are not containing complementary information for data analytics. That is when the physical understanding of the advantages and limitations of the different monitoring systems is not included. Different systems might provide different detection reports that appear to contradict each other. Thus, new AI solutions to deal with heterogeneous data can also support the development of holistic approaches to integrate railway information and make the decision-support models more robust. In addition to the integration of information, data alignment from different measurement trains on a track is another challenge. A robust optimization model is needed to correct positional errors of inspection data from heterogeneous measurements (151).

4.3. Training AI models for maintenance purposes

Railway infrastructures are dynamic, stochastic, and distributed parameter systems that change critical parameters over different locations and times. Moreover, their failures have complex characteristics that result from multiple incidents involving different causalities and uncertainties affecting their functionality, e.g., operational conditions, maintenance activities, weather conditions, traffic loads, the geometry of the infrastructure, and the properties of construction materials (8; 89). Therefore, it is crucial to have an accurate remaining useful life and degradation pattern estimation. An early prediction may result in over-maintenance, and a late prediction could lead to catastrophic failures. Consequently, the existing degradation models for rails have to be updated when new information regarding the health condition of any variable becomes available. However, some models may not be computationally efficient in updating. New models and techniques are needed to alleviate the issue.

To estimate remaining useful life or degradation patterns, many existing models rely on handcrafted features representing degradation processes caused by those factors. The feature selection/extraction often requires domain knowledge and expertise about common causes leading to system degradation. For instance, the location or type of rail surface defects may cause different degradation patterns. The dependency on a large variability of datasets and experimental tests in large railway infrastructures presents a challenge for training in prognostic models. Research in certain applications uses data from run-to-failure tests, from which the labels can be derived (73). For railway applications, it is impossible to conduct such tests. To accurately determine the associated remaining useful life and degradation pattern at every time step for railway infrastructure, the threshold of its failure must be defined. Therefore, some experiential knowledge is needed. For instance, a rail is deemed reliable when the size of rail surface defects achieves a threshold of a certain length (61). As such, condition-based maintenance strategies have to systematically improve to capture new situations and to perform better under new conditions, e.g., when facing new challenges from more intensive use of the infrastructure, climate change, and harsh environmental conditions.

Railway infrastructure systems are also large-scale due to various reasons. Firstly, railway infrastructure often involves many basic components distributed over various kilometers of railway tracks. Further, a railway line can cover a long distance (e.g., over 250 km) with defects that have a size in the order of centimeters (e.g., squats) which their locations are distributed over the whole infrastructure (133). This causes the maintenance optimization problem to become large and intractable. Obtaining an exact resolution of each plan along the prediction horizon is time-consuming and leads to the large-scale optimization problem (2). Secondly, maintenance operations over the whole prediction horizon might change when performing maintenance optimization based on a rolling horizon under real-life conditions. That is, long-term maintenance plans might continuously change according to new predictions and new operation plans. Consequently, the flexibility in the maintenance contracts to include adaptive plans and methods for learning from these plans can be supported with new AI methodologies. Lastly, and most importantly, incorporating the inherent characteristics of the railway system gives rise to a complex nonlinear model that becomes too large and complex to solve efficiently and that leads to a high computational burden (109). For these, the amount of information needed to guarantee the proper operation and the high computational burden of solving problems for such complex and large-scale systems present challenges in research concerning AI. The difficulties include stack overflow and long computation time, and a very challenging-to-obtain set of optimal solutions due to the irregular shape of the resulting Pareto fronts.

4.4. Barriers for AI deployments in the railway industry

Many stakeholders are interrelated within the railway industry. However, they are conservative and usually resist the changes introduced by the digitalization of railway infrastructure, as these can affect the way they worked before. Likewise, the lack of understanding of AI used and the reliability of the results are barriers to the adoption of new methods, especially with regard to safety requirements. Without effective cybersecurity, rail operators cannot be assured of securing their data and information. Consequently, business resources cannot be consolidated, and data are scarce with limited access.

Other aspects that prevent the successful implementation of AI in railway infrastructures also include a lack of standards, traceability, and interpretability of results using complex AI methodologies, particularly neural networks. Results and their implications for the safety of railway infrastructure provided by AI are often difficult to understand. As the infrastructure manager is responsible for his assets and has to ensure the required safe operation, the physical explanation of the problem and the causality are crucial for preventing failures. Failing to provide such information prevents the exploitation of AI methodologies for decision support systems.

Even though there are more applications of AI methodologies in the railway industry, some projects did not have a continuation. The reasons are, firstly and importantly, lack of budget. Secondly, digitalization is not complete and accurate. The railway industry tends to be conservative, and for some inframanagers, the documentation is mainly paper-based. Dynamical models used are primarily in 2D and digital maps of the asset positions are partly not available. This creates a problem of allocating failures when the location of railway infrastructures is not accurate and precise. Therefore, AI developments are needed to check and improve localization accuracy in order to obtain reliable data in the future. Lastly, system integration requires a proper understanding of the system hazards and associated risks. Proper integration of a new system into the current operating system requires to be done in a smooth way and without interrupting the service. Moreover, how to implement AI in real operations is another challenge.

5. Research directions and future opportunities

The challenges discussed previously create a need to develop new intelligent methods based on AI that should be tailored to the particularities of railway infrastructures. This section presents research directions and future opportunities for railway infrastructure. As the use of AI is not yet standardized and their solutions are mostly not traceable and interpretable, implementing AI solutions only serves as a decision-support for railway infrastructure managers at the moment. Humans are still required to make final decisions. We have not yet reached the point of having fully automated AI capable of making final decisions.

Based on our literature review and our view, research directions and future opportunities for railway infrastructure given in Subsections 5.1 - 5.7 are conceivable as there exist current developments in academia. However, further validations in different environments/network lines and standardizations are still needed before reaching a maturity level to be ready for real implementation in the railway industry.

It is noteworthy that some research directions are relatively difficult to achieve in the upcoming years within the context of railway infrastructure. Given the rapid pace of technological development and advancements, making such conclusive judgments about the feasibility and ease of potential research directions in the near future for railway infrastructures is complex and subjective. Therefore, the discussion only serves as an informative and advantageous resource for the readers. Drawing from our perspective, these are transformers (see Section 5.8), metaverse (see Section 5.9), and emerging technologies such as blockchain technology (see Section 5.10). This is because their adoption and implementation are hindered by the unique challenges and characteristics of the railway infrastructures. For instance, many railway infrastructures and systems have been in place for decades. They may have been designed and built using outdated technologies and standards. Introducing new technologies often requires retrofitting or replacing existing infrastructure, which can be expensive, time-consuming, and disruptive. Moreover, integrating new technologies like transformers or blockchain requires careful consideration of how these technologies will interact with existing systems and processes. A skilled workforce with expertise is also required for implementing and maintaining advanced technologies like transformers, metaverse-related solutions, and blockchain where railway organizations may lack the necessary expertise and resources.

5.1. Hybrid models

Hybrid models are promising and have the potential to offer more competitive AI and machine learning models with high performance. Hybrid models refer to a combination of multiple methods or techniques to solve a particular problem. They are developed not only to improve overall performance via their advantages but also to alleviate the limitations of the methods. The models can be constituted by combining 1) different AI methods, 2) human experts and AI methods, 3) physical-based methods or other traditional methods and AI methods, or 4) a mixture of AI, human experts, and physical-based models. Tailoring hybrid models to railway infrastructure applications requires in-depth knowledge of the particularities of the problem and a particular focus on the interfaces between the methods. For example, the performance of probabilistic models in prognosis can be impaired by the accumulating error from using results obtained from diagnosis models based on deep learning. Then, a combination of AI-based models with human-expert or physical-based knowledge is required. In catenary systems, it was mentioned in (85) that, despite the fruitful outcomes of using AI for catenary systems, the growing dependency on data has led to underutilized knowledge of physics accumulated in the past decades. However, the use of AI for catenary systems seldom exploits the physical knowledge to improve the resulting performances. It has been demonstrated that PGMs such as Bayesian networks can consider the underlying physics in inspection data using tailored features (146). Likewise, hybrid multi-scale models can also capture degradation mechanisms for various components involved in the maintenance process while considering some parameters and dynamics determined by data-based approaches. As the methods explicitly include the physical/mechanical characteristics of the infrastructure, the link between data and the physical infrastructure system can be explainable. This helps to improve the interpretability of AI methodologies, particularly neural networks. Therefore, it can be foreseen that AI applications will be even more powerful when combined with knowledge from other approaches. Hybrid models will allow researchers in railway engineering to enhance model effectiveness and get better solutions for railway problems. Moreover, combining AI-based models with human-expert or physical-based knowledge is expected to increase exploitation and reduce resistance to the use of AI in the railway industry.

5.2. Learning methodologies

Learning methodologies are crucial to improving performance based on current and previous experiences systematically. AI methods have been used to learn from current data and performance. However, learning can be continuous based on previous experiences and mistakes. For example, defects that were not detected on time or maintenance decisions that were not correctly prioritized. Learning mechanisms (such as deep reinforcement learning) allow us to systematically include ways to improve our perception and decision mechanism continuously. Learning methodologies provide practical answers to how railway infrastructures 1) can perceive their condition, 2) can make optimal and timely decisions, and 3) can keep learning to improve their performance over time systematically. For these, three promising approaches to learning methodologies are highlighted as follows:

5.2.1. Deep learning

Deep learning has shown the capability to extract highly complex abstractions from different data types and achieved great success in many applications. It is foreseen that deep learning has opened up an opportunity to step beyond the capabilities of a human operator. Deep learning provides a promising direction for big data analytics for assessment and prediction using a tremendous amount of railway data. With the help of deep learning, inspections of railway infrastructures can be fully automated, which fully or partially replaces traditional manual testing and visual inspections. Moreover, computational intelligence methods for expert system design can support railway infrastructure assessment in real time. For instance, in (81), deep learning relying on image-based data that can capture the vibrations of pantograph-catenary interactions and the health conditions of catenary-supporting structures was employed to simultaneously monitor the health condition of catenary components, including contact wires, messenger wires, droppers, and up to 12 types of supporting components. In (64; 21; 86; 162; 35; 79; 150; 88; 84; 90; 57; 82; 83; 117), deep learning was also employed for defect detection and achieved satisfactory results in imaging data. Likewise, recent deep learning-based approaches have significantly demonstrated their capability to fuse information for multi-sensor condition data, including the fusion of static, moving, and crowd-based sensing technologies (106; 10). Various fusion techniques using deep learning algorithms have been proven to assist in learning features from multiple signal sources simultaneously and effectively (20). However, choosing data representations of fused data plays a fundamental role in designing data fusion algorithms. As a result, how to integrate information from multiple data sources and then make a more robust deep learning algorithm is another challenging task for railway infrastructure. In addition to data-based deep learning approaches, physics-informed neural networks (119; 65) have recently emerged as another promising approach for solving problems based on mathematical physics models of railway infrastructures with a small amount of data.

5.2.2. Transfer learning

Within the concept of transfer learning, we can benefit from existing pre-trained models in various ways. Firstly, statistically similar datasets of identical structures can be leveraged to replace the requirement of augmenting a training dataset, especially when some of the actual measurement data are difficult to obtain. In (149), it showed that transfer learning allows the CNN model trained in one domain to the use in other domains where training data are lacking. In (25), transfer learning was employed for evaluating structural conditions of rail in a progressive manner by using acoustic emission monitoring data and knowledge transferred from an acoustic-related database. Secondly, transfer learning has shown its potential to relax the prerequisite for training a deep learning architecture containing up to millions of model parameters. This allows computation time to be reduced, and this facilitates online monitoring of railway infrastructure systems. Thirdly, transfer learning can be used to adapt to work under new conditions where the models have not yet been tested/trained. Due to the impossibility of acquiring training data that represent all operating conditions and fault types, transfer learning is beneficial to make use of information between units or between models. In (98; 148; 24), transfer learning was shown to be able to train models that are robust to newly encountered conditions. This resulted in an improvement in the model performance on the target task. Therefore, transfer learning should be further explored in the field of railway infrastructure, where we aim to apply knowledge from a different railway network to the monitoring and decision-making processes in another network. With transfer learning, intelligent sensing and decision support systems can improve over time.

5.2.3. Deep reinforcement learning

Deep reinforcement learning (DRL) refers to a broad group of learning techniques that emulate how living beings learn by trying actions and learning from successes and failures (100). Its learning process is experience-driven, and its efficiency is enhanced by trial and error to optimize the cumulative reward. In DRL, labeled data are not required, which is beneficial when mainly unlabeled data are available. DRL has shown the potential to handle the dynamic and complex nature of physical problems where solutions to new problems can be adjusted and utilize experience and knowledge learned from solving old problems. For instance, an algorithm developed for track component A can be applied to track component B even though they might be at the same usage level, track tonnage, or environmental situation. In (163), a DRL approach was developed to refine the localization of fasteners in the catenary support to improve an automatic looseness detection method based on deep learning. With state-of-the-art methods, the learning process can be fast and efficient. DRL is also capable of modeling complex stochastic environments and handling relatively high-dimensional problems. It can be used to optimize maintenance and renewal planning by considering cost-effectiveness and risk reduction over a planning horizon and taking into account predictive and condition-based maintenance tasks, as well as time, resource, and engineering constraints (101). However, DRL has not experienced many key developments compared to deep learning. Research on its application to solve problems related to renewal and maintenance planning for railway infrastructure is still limited. As DRL is relatively new to railway infrastructure, its adaptation to solve railway problems has many open challenges, e.g., a major difficulty is data recorded at different monitoring times that is required to train this sort of network. In addition to data-based deep learning approaches, recent advances in physics-informed neural networks have emerged as another promising approach for solving problems based on mathematical physics models of railway infrastructures with a small amount of data.

All in all, by including perception, decision, and learning, the railway infrastructures can be emulated as a living being from where each methodology will contribute to creating its digital brain. However, learning methodologies for railway infrastructures have still been relatively limited.

5.2.4. Metaheuristics

Heuristic optimization is a promising approach for decision-making in railway infrastructure systems. For example, one typical characteristic of maintenance strategies in railways (such as grinding and tamping) is that relaxing strong assumptions of simple models leads to the formulation of more realistic and complex problem formulations. This may create a need for nonlinear relationships between variables which gives rise to a mixed-integer nonlinear optimization problem, especially when discrete decisions are present in a problem. To deal with challenges in maintaining large-scale railway infrastructures, hierarchical and distributed optimization-based methods can be considered. A significant challenge is to speed up the solution of the optimization problems by partitioning and coordination between reduced-size subproblems. Most decomposition-based approaches work by decomposing the large-scale multi-objective optimization problem into multiple single-objective subproblems based on a set of weight vectors. Then, the subproblems can be solved cooperatively in, e.g., an evolutionary algorithm framework. Stochastic optimization for decisions in rail systems explicitly includes the effect of different sources of stochasticity and uncertainty, such as in measurements, loading conditions, infrastructure parameters, and external factors, including climate/weather. Multi-objective decision-based methods for dynamic decision support tools in railway infrastructure systems help find different solutions, typically to quantify trade-offs between cost reduction and performance. But they can include punctuality, efficiency, robustness, safety, sustainability (recycling/disposal), energy consumption, etc.

5.3. Digital twins

When only limited data are available and they are imbalanced, transfer learning, on the one hand, can be considered to alleviate the issues arising from using small datasets to train machine learning models. On the other hand, it is crucial to have a sufficient amount of data. When it is not possible to collect real data, particularly data related to rare events, e.g., failures or defects, using synthetic data is an option. A digital twin can be a good candidate for that.

Digital twins are a conceptual framework for interconnecting a physical system and its digital representations (140). Digital twins are created by capturing and integrating various data types from sensors, devices, and other sources, including physical models. The purpose is to gain deeper insights into the physical entities they represent. Digital twins allow us to emulate future scenarios of the consequences. This helps us with risk assessment and decision-making to prepare for and mitigate the impact of rare events. Within this context, an open challenge that needs to be addressed is an effective method to generate synthetic data representing the total variation of the expected railway operating conditions.

In (76), a building information model (BIM) was used to photo-realistically simulate severe structural damage in a synthetic computer graphics environment. In (69), a deep learning-integrated digital twin model was developed to establish an interoperable functionality and to develop typologies of models described for autonomous real-time interpretation and decision-making support for the architecture, engineering and construction sector. By applying the concept of digital twins to railway infrastructure, railway companies can cut costs, modernize workflows, and increase efficiency and performance. Digital twins allow companies to offer new services such as remote monitoring, real-time diagnostics, predictive maintenance, and automated operations. With a combination of various sensors throughout the whole infrastructure, information can be immediately analyzed by AI and big data to plan maintenance actions proactively. This can avoid incidents or delay and improve safety and operational efficiency.

While digital twins bring numerous opportunities to the railway industry, they present challenges in their implementation. To successfully implement digital twins in railway infrastructure, sufficient data need to be available for properly calibrating digital twins. Moreover, a new mindset of rail operators and authorities must be developed; they must promote cooperation, share data, and consolidate business resources. Also, business models need to be changed, and, most importantly, financial investments and a strategy to tackle cyber threats are required (9).

5.4. Multidisciplinary research for holistic approach

Railway infrastructure research is inherently multidisciplinary. Answering fundamental questions in the field requires knowledge from different fields. Combined with AI, some of the emerging fields related to resilience engineering, climate change, cyber security, etc., are essential for solving open research questions. For example, AI research related to an embankment requires knowledge of geosciences, railway engineering, and computer sciences, among other fields. Without knowledge sharing and research collaborations, the essential physics and dynamics of the infrastructures cannot be studied efficiently. When considering the whole life cycle of the railway infrastructure, environmental and social impacts add more dimensions. This requires a holistic approach to analyze different aspects of the overall life cycle cost to evaluate the system's environmental, economic, and social performance. For instance, the study in (49) showed that the operation and maintenance phases are responsible for most emissions, with electricity consumption being the primary contributor. Energy costs were identified as the main contributor (92%) to the overall life cycle cost, and reducing these costs could help lower the system's total cost. The social impact assessment in (49) revealed that the urban transportation industry has strong connections with consumers, workers, the local community, and society. Even though new AI technologies can be employed to assist learning, they can extract valuable insights, patterns, or relationships from the data without human dependency. When no historical data is available, physical models are needed. In the field of railway infrastructure, 3D dynamic models are widely used as they offer dynamics and physical interpretation of the systems. However, when it comes to a complex non-static problem, e.g., soil (157; 3), a new dynamical model and sensing technologies are needed. The lack of historical data and efficient higher-dimensional dynamic models results in less research on some railway components, e.g., substructures and embankments. However, this also opens up opportunities for AI approaches in the areas with few data when the available physical knowledge can be included.

5.5. Validity of the data

Many existing studies developed AI methodologies using training data under specific environments and operating conditions. Ultimately, we aim to develop innovative solutions that can facilitate the work of infra managers so they can focus on other critical challenges. To ensure the robustness, generalization, and efficacy of the new methodologies, the validity of the data sources and field validations are required. It's essential to regularly and continuously assess and measure the impact of data to ensure they deliver tangible results that meet the needs of rail operators. Accurate and reliable data serves as the foundation for making informed decisions. For example, can we trust the decision driven by the data we use to train the model? Moreover, more controlled field measurements and shared case studies should be provided so that the researchers can validate and compare the performance level of their models developed with the state-of-the-art methods in the field of railway infrastructures.

5.6. Interoperability of the data

In the railway industry, data interoperability appears to be a significant challenge in delivering AI-based solutions. Its problem is how to convert and integrate the data between different systems, e.g., the data coming from the APIs of different customers. Each API has its own way of working. Having compatibility among software is thus critical to facilitate the use of AI. A data standard is also required to enable the available interactions between heterogeneous formats and systems.

5.7. Cloud infrastructures

Digitalization in railway infrastructures generates a large volume of real-time data as many devices and sensors are used to monitor the assets. This data can provide insights into the health conditions of the monitored assets, and this enables predictive maintenance. To derive actionable insights in real-time, cloud infrastructures need to be invested and leveraged. With such big data, the communication network and the adoption of 5G technology are required. A petabyte-scale Internet of Things and edge data to the cloud must be agile. The adoption of edge computing is required for the use of machine learning and AI algorithms to help manage the infrastructures in near real-time.

5.8. Transformers

Transformer models refer to a specific type of deep learning networks. They are designed with large encoder and decoder blocks based on a self-attention mechanism which represents the key innovation that allows transformers to selectively focus on different parts of the input sequence (144). Instead of relying on sequential processing, transformers process the entire input sequence in parallel. Before transformers arrived, users had to train neural networks with large labeled datasets that were costly and time-consuming to produce. By finding patterns between elements mathematically, transformers eliminate that need. Even without pre-training on large datasets, transformer-based models are more robust to generalization (12). Therefore, transformer models have opened up another technique to tackle insufficient and imbalanced railway data. This allows more researchers in railway engineering to conduct research with machine learning without facing issues arising from the training data. However, transformer models themselves can contain trillion parameters, e.g., Googles Switch Transformer has 1.6 trillion parameters (38). This poses another challenge in training transformer models that require further research.

5.9. Metaverse

Metaverse is a concept referring to a virtual world where users can interact with each other and computer-generated environments in real time. The concept of the metaverse often involves a combination of technologies such as virtual reality (VR), augmented reality (AR), artificial intelligence (AI), blockchain, and other emerging technologies, e.g., robotics and drones. Even though the metaverse is currently used for entertainment and gaming, it has the potential to be applied in the railway industry.

By using technologies that are equipped with cameras, IoT devices, and sensors that collect real-time data from instrumented railway infrastructure, data obtained can be analyzed by AI and can be used to create virtual environments. Many aspects of real fieldwork that transcend physical limitations can be created. For instance, to create a virtual environment from information collected in areas that are difficult to access and risky to humans. This enables railway infra managers to conduct virtual inspections, identify issues, explore, analyze, and optimize various aspects of the railway infrastructure, e.g., design, operation, and maintenance. However, applying the metaverse in railway infrastructure is still an emerging concept, and its full potential is yet to be explored.

5.10. Emerging technologies

Several emerging technologies can contribute to improving the reliability of railway infrastructure. Examples include blockchain technology, robotics, and drones. Blockchain technology can enhance the reliability of the supply chain management process in the railway industry. It can provide transparent and tamper-resistant records of the origin, maintenance history, and certification of critical components, ensuring the integrity and reliability of the infrastructure. Robots and drones, equipped with cameras and sensors, can be used to regularly inspect railway tracks, bridges, tunnels, and other infrastructure components. They can provide detailed visual data and collect information in areas that are difficult to access and risky to humans. In addition to the aforementioned trends, further potential technologies can include web3, cryptocurrencies, nonfungible tokens, natural language processing, 5G or 6G technology, conversational AI Humans, etc. These emerging technologies have the potential to revolutionize the railway industry by improving reliability, safety, minimizing various types of risks, and enhancing the overall performance of the railway infrastructure. However, their use cases and implementation will depend on technological advancements, industry requirements, and regulatory considerations on planning and integration with existing systems.

6. Conclusion

This paper reviews some AI methodologies developed and integrated into railway infrastructures to tackle problems arising from its usage and natural degradation mechanisms. The methods focused on in this paper are neural networks, metaheuristics, regressions, probabilistic graphical models, clustering, fuzzy logic, and transfer learning. Based on our survey of journal papers on Scopus, they have shown great promise for various applications in railway infrastructure. Not only at a research level but many of these AI and ML applications have also been implemented in the railway industry, in which the extent of their implementations varies across different railway operators and regions. Despite their success, the use of AI methodologies exhibits certain limitations that pose challenges for a successful implementation in the railway industry. Some considerations and discussions about the challenges and the need for new intelligent methods are presented in this paper to bridge the gaps between industrial applications and new AI developments. Researchers in academia and industry can exploit the information from our paper to visualize trends and to develop benchmarks of problems and methods tailored to the particularities of railway infrastructures. Finally, we aim with this paper to also inform the railway industry about the overview of technological advances in the field of AI, so even more innovative use cases and applications can emerge in the near future. In addition to the enthusiasm surrounding the implementation of AI in railway infrastructure, it is imperative to prioritize economic efficiency and feasibility. For instance, the existing maintenance and operational protocols rely on predefined rule sets, which would necessitate modifications when incorporating solutions provided by AI technologies. Consequently, alongside technological advancements, a fundamental redesign of inspection, monitoring, and maintenance procedures becomes essential.

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