Artificial Intelligence in Railway Transport: Taxonomy, Regulations, and Applications

Nikola Bešinović, Lorenzo De Donato, Francesco Flammini, *Senior Member, IEEE*, Rob M. P. Goverde, *Member, IEEE*, Zhiyuan Lin, Ronghui Liu, Stefano Marrone, Roberto Nardone, Tianli Tang, and Valeria Vittorini

***Abstract*— Artificial Intelligence (AI) is becoming pervasive in most engineering domains, and railway transport is no exception. However, due to the plethora of different new terms and meanings associated with them, there is a risk that railway practitioners, as several other categories, will get lost in those ambiguities and fuzzy boundaries, and hence fail to catch the real opportunities and potential of machine learning, artificial vision, and big data analytics, just to name a few of the most promising approaches connected to AI. The scope of this paper is to introduce the basic concepts and possible applications of AI to railway academics and practitioners. To that aim, this paper presents a structured taxonomy to guide researchers and practitioners to understand AI techniques, research fields, disciplines, and applications, both in general terms and in close connection with railway applications such as autonomous driving, maintenance, and traffic management. The important aspects of ethics and explainability of AI in railways are also introduced. The connection between AI concepts and railway subdomains has been supported by relevant research addressing existing and planned applications in order to provide some pointers to promising directions.**

***Index Terms*— Artificial intelligence, railway transport, machine learning, computer vision, traffic management, predictive maintenance.**

Manuscript received 1 April 2021; revised 12 September 2021; accepted 27 November 2021. Date of publication 15 December 2021; date of current version 12 September 2022. This work was supported in part by the Shift2Rail Joint Undertaking under the European Union's Horizon 2020 Research and Innovation Programme under Grant n.881782 RAILS. The work of Zhiyuan Lin and Ronghui Liu was supported in part by the Assisted Very Short Term Planning (VSTP)/Dynamic Timetabling Project funded by U.K. Rail Safety and Standards Board (RSSB) via Bellvedi Ltd., under Grant RSSB/494204565. The Associate Editor for this article was J. Xun. *(Corresponding author: Zhiyuan Lin.)*

Nikola Bešinović and Rob M. P. Goverde are with the Department of Transport and Planning, Delft University of Technology, 2600GA Delft, The Netherlands (e-mail: n.besinovic@tudelft.nl; r.m.p.goverde@tudelft.nl).

Lorenzo De Donato, Stefano Marrone, and Valeria Vittorini are with the Department of Electrical Engineering and Information Technology, University of Naples Federico II, 80125 Naples, Italy (e-mail: lorenzo.dedonato@unina.it; stefano.marrone@unina.it; valeria.vittorini@unina.it).

Francesco Flammini is with the School of Innovation, Design and Engineering, Mälardalen University, 72220 Västerås, Sweden, and also with the Department of Computer Science and Media Technology, Linnaeus University, 35195 Vaxjo, Sweden (e-mail: francesco.flammini@lnu.se).

Zhiyuan Lin and Ronghui Liu are with the Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, U.K. (e-mail: z.lin@leeds.ac.uk; r.liu@its.leeds.ac.uk).

Roberto Nardone is with the Department of Engineering, University of Naples "Parthenope," 80143 Naples, Italy (e-mail: roberto.nardone@uniparthenope.it).

Tianli Tang is with the Jiangsu Key Laboratory of Urban ITS, Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, School of Transportation, Southeast University, Nanjing 211189, China (e-mail: t-tang@seu.edu.cn).

Digital Object Identifier 10.1109/TITS.2021.3131637

I. Introduction

It IS now widely accepted that Artificial Intelligence (AI) is influencing almost every bit of our life. A survey from Economic Intelligent Unit (conducted in late-2016) found that 44% of executives said delaying AI implementation will make their business vulnerable to new, disruptive tech start-ups [1]. Railway is no exception. Although AI is still in its very infancy for the railway sector, there is certain evidence showing that its potential should not be underestimated. For instance, Torsino *et al.* [2] listed several facets in railways where AI can play an important role: customer service, optimisation of complex railway systems, and improving safety and security of urban rail networks. They concluded that "It is clear AI systems can be powerful and can solve the critical challenges that railways are facing today." Gilbert *et al.* [3] stressed the importance of AI for the future railway industry and believe that AI will soon become a common tool used throughout the rail industry. Several topics are discussed where AI is supposed to act as a game-changer for the railway sector, such as capacity management, life cycle cost, maintenance, reducing error from both humans and computers, high-level automation and auto-adaptive systems. In essence, many AI experts and railway practitioners believe that the role of AI in the railway sector will become more and more influential, and a pivoting time where AI is used as a common tool will be seen in the future.

In recent years, the term Artificial Intelligence has increasingly become an integral part of daily life in the form of smartphones, intelligent vocal assistants, etc. However, due to its widespread use, the term AI is often improperly used as a synonym of closely related concepts such as Machine Learning, Deep Learning and Big Data. Thus, there tends to be a lack of clear consensus on what AI represents and thus much confusion and misunderstanding among researchers and practitioners exist in both academic literature and public communications [4], [5].

A taxonomy is a means of classifying entities according to their natural relationships. It provides a common vocabulary to discuss and share information about a specific topic. We find examples of taxonomy papers in different fields including supply chains [6], aviation [7] and manufacturing [8], and in railways, on taxonomy for performance of railway operations [9], mechanical energy harvesting [10], development of mass transit systems [11], and communication errors in maintenance [12]. Similarly, researchers focused commonly on specific subdomains of AI and proposed taxonomies in different fields. For example, a taxonomy has been defined for 6G communication networks (addressing among others ITS) [13], supervised regression learning for road traffic forecasting [14], supervised learning for intrusion detection systems in SCADA environments [15], evolutionary algorithms in road transport [16], and in railways specifically, taxonomy on machine learning and deep learning railway track predictive maintenance [17], [18]. However, a holistic view on AI in railways does still not exist. Also, a general AI taxonomy suited to railway transport and transport in general is missing. Our contention is that an important use of a taxonomy for AI is to inform researchers and practitioners about which methods are appropriate to assist with decision-making in railway domains.

This paper aims to define AI, introduce taxonomy and make necessary relations between AI and railway transport. The goal of the paper is to bring together two domains and the corresponding experts from AI and railways and define AI for the railway domain. This would pave the way for a better understanding of terminology and concepts of AI to railway industry on one side, and introduce railway subdomains to AI experts. This detailed taxonomy of AI is complemented by a survey of AI used in railways. In addition, a focus is placed on research niches that are still unexplored by the communities in different railway subdomains. The open issues and research directions for the implementation to railways endowed with artificial intelligence are also discussed. In fact, we not only give high-level future directions but also support it with some existing research from similar (transport) domains, wherever it is possible.

The remainder of the paper is organised as follows. Section II presents the methodology for mapping railway transport to AI. Section III gives a definition of AI from the perspective of the railway transport domain. Section IV introduces a taxonomy of AI. Next, Section V reports relevant guidelines and regulations on AI, including ethics and explainability, and identifies their particular importance for railways. Section VI gives the mapping results of AI approaches applied to railway problems (VI-A), and presents the existing challenges for future AI applications in railways for specific subdomains (VI-B and VI-C). In particular, VI-B highlights the new problems that are more tangible and could be tackled by extending approaches from similar domains, and VI-C highlights the more challenging (out-of-the-box/greenfield) research directions, i.e., research that has not been addressed in comparable domains. Finally, Section VII brings final concluding remarks.

II. Methodology

We aim to uncover the use of AI in railway systems with the goal of highlighting already existing as well as potential applications. This section describes the applied methodology for mapping these current usages and future opportunities of AI in railways. The focus is on the railway transport subdomains including 1) maintenance and inspection, 2) safety and security, 3) autonomous driving and control, 4) transport planning and management, 5) revenue management, 6) transport policy and 7) passenger mobility. In addition, to identify promising potential research, we also looked into related domains such as other transport modes (e.g. road and air), supply chain and manufacturing. To showcase a structured overview of these current and potential research, we map railway subdomains to different classes of AI, based on an AI taxonomy introduced in Section IV.

For finding relevant papers, we searched journal and conference papers using the Scopus database. Also, we enriched the search with successful real-world applications in professional magazines and technical reports, for which the Google search engine was used. Still, scientific papers form a great majority of the reviewed documents. The keywords used were designed as a combination of a term from AI context and a term from railway domain context, also ‘railway’, or another domain, is added where needed. For example, a string consisting of ‘expert systems’, ‘passenger mobility’ and ‘railway’ was used. Sometimes, for a single AI or railway context, the keywords may be separated in the search, e.g. ‘safety’ and ‘security’ were used separately. In addition, terms like ‘ethics’ and ‘explainability’ were considered as well.

For mapping, we build matrices showing the intersections between railway and AI. For each cell, we define its current state representing whether it is recognised in scientific research and/or in practice. To do so, each cell receives certain (Y), potential (P), or uncertain (U) based on the corresponding match. Where appropriate, the relevant papers, i.e. from railways or other domains, are given to support the conclusion of a cell. We determine whether an entry in the three tables belongs to Y, P or U by the following rules:

- Y: Applications of the exact match are found in academic journal/conference papers and/or successful real-world applications are found in magazines/news or other media.
- P: Similar applications of the match are found in academic journal/conference papers and/or real-world applications. For instance, an application of AI in another sector other than rail but the principles are possibly transferable.
- U: No explicit literature/report/applications can be found by the databases, even from other related domains. In addition, we use our own judgement based on the expertise and experience of the authors.

In essence, the cells marked Y represent existing AI research in railways. Instead, the cells with P and U represent future research directions that are worth considering for more detailed investigations, some of which could be possibly transferred with more ease from related domains (Ps) than others (Us). The results of this mapping are presented in Section VI.

III. A Definition of Artificial Intelligence

In order to highlight the potential of AI in railways, it is essential to provide a comprehensive definition of what AI actually represents and justify why future intelligent railways are expected to be different compared to traditional railway automation systems, including automatic train protection and legacy driverless systems. A basic definition associates AI to any machines acting in a way that seems intelligent [19] or exhibiting characteristics that are typical of human reasoning. In other words, according to this general definition, the research on AI aims at creating intelligent agents that think and act like humans. The main limitation of such a definition is the lack of a universally accepted definition of 'intelligence'. Conceptually speaking, intelligence refers to the ability of an agent (e.g. a human being) to learn, understand, reason, plan and solve problems. These aspects are very hard to quantify, describe and measure in a quantitative way. Therefore, in the context of the AI domain, one of the most common definitions of intelligence is based on the ability of an agent to pass 'the imitation game', also known as Turing test [20]: a machine is deemed intelligent if it is indistinguishable from a human during an interaction with an impartial observer.

Over the years, more structured and detailed definitions have been introduced, e.g. [19], [21]–[23]. Interestingly, they are very similar in some aspects (e.g. the ability to learn from experience or to take autonomous decisions) while tend to differ when it comes to defining in which 'shape' AI can be deployed (e.g. robot, software program, electronic computer, etc.). These existing definitions were trying to capture the broad nature of AI and its potential coverage of various domains and areas. By doing so, for certain domains, such definitions may be too abstract and they could be difficult to grasp and thus would not be widely accepted. Therefore, these aspects of such general definitions tend to reduce its uptake leading to no common agreement on what AI actually represents.

To address this challenge, we need a definition of AI which is suitable to support next-generation railway transport and traffic engineering. To this aim, we need to stress some aspects that are crucial when considering AI application in the railway domain: 1) Being able to learn from experience and adapt to the environment (e.g., energy optimised driving and obstacle detection through artificial vision and other sensors adapting to changing environmental conditions and learning from driver's behaviour and past reactions); 2) Take autonomous decisions in uncertain scenarios by interacting with other intelligent entities (e.g., cooperative driving, including virtual coupling, through train-to-train communication); 3) Accomplish tasks that would require critical intelligence if done by a human (e.g., reputation-based multi-source information fusion for safety/security decision making); 4) Exclude trivial automation that does not take account uncertainties and/or unexpected scenarios (e.g., non-defensive and non-robust railway automation approaches that do not support holistic fault-tolerance, resilience, and self-diagnostics/self-healing); and 5) Suitable to hardware, software, or hybrid implementation at multiple edge, fog and cloud computing levels (e.g., digital twins implementing machine learning models for data-driven predictive maintenance by monitoring a large number of similar railway infrastructure and rolling stock).

One possible definition accounting for those aspects is the following: *AI is the discipline gathering all the aspects that allow an entity to determine how to perform a task and/or take a decision based on the experience matured by observing samples and/or by interacting with an environment, possibly competing against or cooperating with other entities*. The term *aspects* refers to algorithms, theoretical formulations and computational technologies (both hardware and software) directly or indirectly designed to make an entity accomplish a task that would require intelligence if accomplished by a human. The term *entity* refers to both purely software, purely hardware and any hybrid variants of the two (e.g. a software, or a robot, or a virtual agent). The phrase *experience matured* is explicitly intended to include both the concepts of learning (i.e. gain new knowledge from some example) and of data-driven inference (i.e. inferring consequences from some priors).

All the factors we stressed above are essential to characterise AI in railways since they allow us to exclude from the class of future intelligent railways all the widespread approaches using a coded (i.e., programmed by someone) automatism. An example of this is current driverless trains, which implement Automatic Train Operation (ATO) together with Automatic Train Protection (ATP) to safely perform a series of well defined actions, according to some predefined rules and schedule [24]. According to the provided AI definition, those driverless trains cannot be considered as intelligent systems because they do not have the capacity to take autonomous decisions in the presence of uncertainties or unexpected scenarios, learn from experience, adapt to changes in the environment such as obstacles on the track, etc. Instead, the provided AI definition includes all algorithms designed to perform data-driven problem-solving and decision-making which are expected to have a huge potential and impact in future railways.

In addition, AI-supported railways can benefit from other smart domains such as smart cities [25] and smart transport/ITS [26], [27]. For example, real-time predictions of customer demand and other traffic modes conditions could provide services more efficiently, timely and sustainably. Also, it will allow better interaction with other public transport modes involving on-demand shared systems (e.g., shared taxis, flexible car sharing, shared bikes) for better door-to-door journeys. Simultaneously, smart cities and ITS can be powered by railway AI applications. For example, smarter railways will help to understand holistic traffic and city conditions in normal statuses as well as during emergency situations (disruptions, accidents, adverse weather). For example, it could provide information about incidents on a railway network in order to increase the responsiveness of a smart city transport system. Also, it will increase mobility and city dynamic flows of future interconnected smart cities and lead to seamless connections and faster journeys.

When focusing on AI as a discipline, we need to define a set of means, techniques, applications, etc., interconnected with each other, in order to define AI as a whole. Therefore, Section IV provides an AI taxonomy including the main components and their interrelations.

In addition, certain research areas that are related to AI tend to be mixed with AI and/or introduced as equal. Some examples are digital twins, big data, and augmented reality. **Digital Twins** represents a set of tools, means and procedures born with Computer-Aided Design (CAD) systems with the

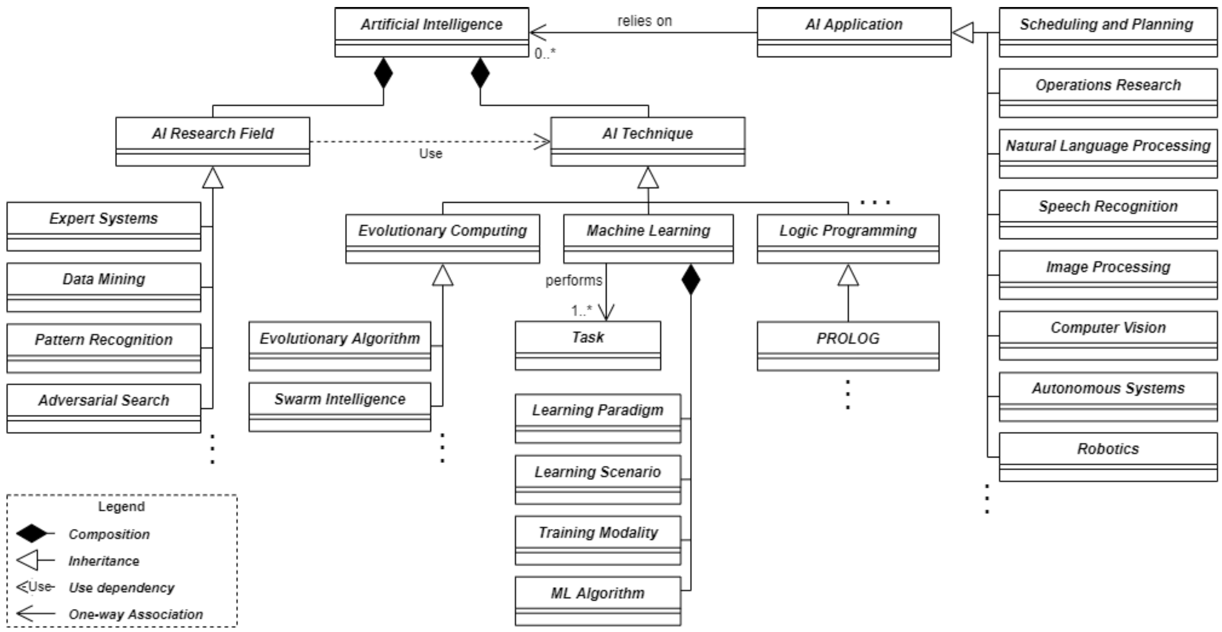


Fig. 1. Artificial intelligence taxonomy class diagram.

aim of realising the digital version of an entity under analysis. **Augmented Reality** (AR)[1] is a sector that is living a growing interest for both entertainment (e.g. video games) and professional (e.g. remote medicine) applications. **Big Data** represents a discipline associated with the collection, manipulation and analysis of huge, varied, valued and heterogeneous (typically non-structured) amounts of data.

IV. AI Taxonomy

Having introduced our definition for AI in the railway domain, also taking into account essential requirements of future intelligent railways, this section defines an AI taxonomy with the aim of framing the complexity of AI terminology. The taxonomy is represented by a UML class diagram, which allows for a more formal and effective representation [28].

The proposed taxonomy consists of three main concepts:

- **AI Technique**, representing methods, algorithms and approaches enabling systems to perform tasks commonly associated with intelligent behaviour, e.g. machine learning, evolutionary computing;
- **AI Research Field**, representing research areas that rely on AI techniques and would not exist without them, e.g. expert systems, data mining, pattern recognition;
- **AI Application**, representing cross-domain applications that leverage AI to improve performance and usability, e.g. computer vision, speech recognition, planning and scheduling.

The class diagram is depicted in Figure 1, where classes represent concepts of our taxonomy. Example of classes, according to the definitions given above, are Artificial Intelligence, AI Research Field, AI Technique and AI Application.

[1]The considerations made also stand for virtual and mixed reality.

Among the concepts, different kinds of relationships can exist. Black rhombi identify compositions, that are whole/part relationships, where, if a composite is deleted, all other parts associated with it are deleted. An example is the composition between Artificial Intelligence and AI Technique, with the aim of stressing the fact that, without AI, the latter cannot exist. Full arrows with solid lines represent inheritances, which model concepts with a generalization hierarchy. For example, there is an inheritance of PROLOG from Logic Programming, to indicate that the former inherits all the properties (including connections to the other elements) from the latter, adding to them its own characteristics. Dotted lines represent dependencies (weak relationships), while solid lines indicate associations (strong relationships), where the navigation direction is represented by the arrow itself. For example, the *use* dependency between AI Research Field and AI Technique indicates that the former may use the latter to accomplish its goals. Similarly, the *relies on* association between AI Application and Artificial Intelligence indicates that the former is strongly depended on the latter. In both cases, numbers at the sides of a line represent the cardinality of the relationship. For example, *0..** on the left side of the *relies on* association indicates that there may be (or not) AI Applications relying on AI, i.e. taking advantage of any AI Research Field or AI Technique. For example, according to such definition, a mathematical rail traffic optimisation model (e.g., one coming from Operations Research) on its own, may be considered as not "intelligent". Instead, it would become "intelligent" when combined with an AI technique.

It is worth highlighting that we primarily focus on potential railway applications, based on the definition we provided in the previous section. Moreover, as AI is constantly evolving and possibly new concepts would need to be added as they emerge, the proposed taxonomy is flexible and intended to accommodate newly rising concepts. The following of this section detail the main classes of our AI taxonomy. A more extensive description of the AI classes is given in [29].

A. AI Techniques

Defining artificial intelligence is usually about making a machine able to do something that would require intelligence if done by humans. In AI Technique we gather all the means, algorithms and disciplines that allow an artificial entity to perform such intelligent tasks. There are three main subclasses. First, Evolutionary Computing focuses on the algorithms and techniques inspired by biological evolution such as e.g. evolutionary algorithms, swarm intelligence. Second, Logic Programming represents a set of programming paradigms based of first-order logic to infer new knowledge starting from some priors such as PROLOG. Third, Machine Learning represents an integrated concept that satisfies the following rationale: Machine Learning can perform a given task by means of a specific ML Algorithm trained by using a specific Learning Paradigm, in a particular Learning Scenario, and considering a fixed Training Modality. Hence, the class Task defines the goal that the user wants to obtain such as classification, regression, and clustering. ML Algorithm represents the sequence of operations used to train a specific model such as support vector machines, tree-based, Bayesian, and artificial neural networks. Learning Paradigm refers to the strategy used to guide the algorithm during the learning process such as supervised, unsupervised, and reinforcement learning. Learning Scenario describes the distinctive characteristics of the task under analysis such as multi-task, single-task, and one shot. Lastly, Training Modality indicates how the training phase is implemented as the transfer of knowledge from another task/domain (transfer learning), and the training from scratch.

B. AI Research Fields

The term AI Research Field refers to domains, disciplines or research areas born with or under the AI umbrella, and that can not exists without it. In particular, the term refers to those fields in which the use of AI is not a matter of performance or effectiveness, but the core of the field itself. Some notable examples, represented as UML classes, are: Expert Systems, the branch of AI focusing on software intended to emulate the decision process made by experts in some fields (e.g. physician for medical imaging); Data Mining (DM), the set of procedure intended to mine information from raw data; Pattern Recognition, the discipline studying how to recognise, detect and discriminate samples by leveraging patterns in data; Adversarial Search, the study of environments where agents act in an environment populated with other adversaries. DM is an essential step of the *knowledge discovery from data* process and aims at extracting information from data (potentially voluminous and heterogeneous datasets [30]) by leveraging intelligent methods [31] (i.e. ML). In our taxonomy, we kept DM detached from ML as DM focuses more on “discovering” and “extracting” knowledge from data, while ML focuses on “learning” from data to perform actions.

C. AI Applications

In the proposed class diagram (Figure 1), AI Application is connected to AI by means of a one-way association, meaning that the former uses the latter (and not the other way round). Within this class we gather all the domains, research areas, topics, etc., that are not strictly bounded to AI. Nonetheless, they are increasingly relying on AI, to the point of starting to be (wrongly) considered feasible only with AI. The set of AI applications is extremely wide. Among all, some of the common ones are Scheduling and Planning, the set of tools leveraging AI for arranging activities and operations, Operations Research, and in particular its sub-fields leveraging AI to improve optimisation procedures, Natural Language Processing and Speech Recognition, the ability of a system to understand and produce non structured texts or voices, Image processing and Computer Vision, including image acquisition, processing, inferring, etc., by means of an AI algorithm, Robotics, the set of algorithms designed to govern a robot.

V. Guidelines and Regulations

Ethics and explainability in AI represent two of the topics that raise more concerns to EU citizens. For this reason, existing guidelines on these topics need to be addressed and discussed with reference to the seven railway subdomains introduced in Section III.

According to the guidelines introduced by the AI High-Level Expert Group [32], trustworthy AI must be **lawful**, meaning that it must respect all applicable laws, norms, and regulations; **ethical**, meaning that it should respect ethical principles and values; **robust**, from both the technical perspective and taking into account its social environment. Moreover, in order to be deemed trustworthy, AI systems should follow the human-centric approach, meaning that the final decisions shall be left to people, the command and responsibility chain should be reconstructable, AI applications should be fail-safe and it shall benefit human beings, including future generations.

Due to the advancement of technology, results obtained in safety-critical systems, like railways, are not easily interpretable [33]. New initiatives towards Explainable AI (XAI) [34] are rising and becoming ever important. XAI refers to methods and techniques to make outputs understandable by humans. XAI deals with three particular and different concepts: **Interpretability** (also called **Transparency**) is the characteristic of a model to be at a level that makes sense for a human observer, so enabling interventions aimed at taking impartial decisions and improve robustness; **Explainability** is the characteristic of a model to take actions and procedures for clarifying its behaviour; **Comprehensibility** is the characteristic of a model to represent its learned knowledge in a human-understandable fashion.

It is clear that transport and railways are generally relevant sectors to consider ethical and explainability aspects. However, not all the applications pose risks of such significance to justify legislative intervention. It is thus necessary to focus attention on the specific application by evaluating its potential risks and impacts on human beings, wellness, and the environment. In general, with respect to the railway subdomains, we could say that in most of them AI could have mostly a minor/medium impact on the wellness of human beings and the environment, and major only in some subdomains. A minor impact can be expected in all the subdomains except for those directly affecting the safety of people, which are safety and security, and autonomous driving and control [35]. For instance, an AI application aiming at reducing the replacement of consumable components (e.g. rails, switches, rolling stock) does not require a significant legislative intervention, even if it could offer benefits to special waste disposal and to environmental pollution. At a medium level, also ethical concerns arise from applying AI to staff scheduling such as drivers, crew, and maintenance workers. In an ideal AI-based staff schedule, the efficiency of an operational plan and the rights of staff well-being such as having appropriate breaks and working patterns should be well balanced. Similarly, we can imagine several applications of AI in all these subdomains with a minor/medium impact on the wellness of human beings and the environment, but where ethical concerns from the application of AI subsist.

Finally, a strong impact on ethics and a significant legislative intervention would be required in the two subdomains cited above. For example, the braking decision when approaching an obstacle of automated driving systems is a typical target application where the balance between the highest safety and the passengers' comfort is unstable. The questions that could arise include: What is the right decision for an AI system, for instance, applied in obstacle detection, to mitigate the effect of false positives? And, what is the right decision for the same system when an animal or a road vehicle is detected on the track? These are just two of the possible questions that arise when starting to think about the potentials of AI in railways. For example, in road transport, [36] highlights key ethical issues in the use of AI in automated driving; while [37] discusses the dangers of the Moral Machine (MM) experiment in Autonomous Vehicles, alerting against both its uses for normative ends and the whole approach it is built upon to address ethical issues. Further lessons on ethical issues of AI can be learnt from other sectors, such as healthcare [38] and robotics [39].

Looking at the explainability of AI, it shall be considered when developing models and systems across the whole railway transport, without distinction between the subdomains. So far, XAI has not gained attention in railway transport, with an exception of [40]. In [40], the problem of discerning different reasons for the occurrence of train delays is studied. In particular, methods from XAI help to classify to which amount the primary and secondary features contribute to a specific prediction of the model. For other domains, a comprehensive review of XAI in various business and industry sectors is given in [41], where case studies are reported in recommendation systems, sales, lending, and fraud detection. An article [42] on Supply Chain Brain discusses the XAI issue in supply chains. These can be used to build on and define an important aspect of XAI for railways.

Overall, we could say that surely the subdomains of safety and security and automated driving and control shall receive greater and immediate attention from the legislative point of view, while ethical concerns could arise also from AI applications in all other subdomains as, for example, control and staff scheduling. Finally, explainability aspects shall be addressed in all subdomains.

VI. Mapping AI to Railway Applications: Current Research and Opportunities

We give three matrices showing the intersections between railway subdomains and AI research fields, techniques, and applications, respectively. Table I gives intersections with AI research fields, Table II gives intersections with AI techniques and Table III gives intersections with AI applications. Section VI-A describes the existing AI research in railways, marked Y in the tables. Section VI-B represent potential future research, marked P. Finally, Section VI-C gives cells that currently do not have recognised relevant research, marked uncertain U, but which are worth considering for more detailed investigations, and which could lead to more substantial research advances for both railways and AI.

A. Existing Applications

We give existing applications of AI in railways per subdomain as defined in Tables I-III.

1) Maintenance and Inspection: Applications of AI in railway maintenance and inspection have been developed for addressing infrastructure (e.g. [47]) and rolling stock (e.g. [103]). Reference [43] gives a survey on applications of visual inspection based on image processing in the railway industry and sets the future research directions of visual inspection technology. [44] gives a review on the application of various AI and expert systems for fault diagnosis of high-speed railways, while [110] reports the pioneering work in autonomous systems for condition monitoring of railway infrastructure. In [47], the Dutch infrastructure manager ProRail uses pattern recognition and image processing technology to predict where and when a malfunction will occur in switches. The switches are equipped with sensors that transmit information about the power consumption, vibrations and heat of the switches. By analysing the generated data, the prediction can be realised before a disruption would happen. Machine learning and Deep Learning approaches have found great applicability for Defect Detection and Prediction tasks [83]–[85].

In [103], a preventive maintenance (PM) scheduling problem for a rolling stock system is considered. The goal was to determine the PM interval for components in a rolling stock system. The total expected costs for the system life cycle and system availability are used as optimisation criteria.

2) Safety and Security: Most of the AI (research fields) have been recognised in the sub-domain of safety and security including incident analysis and station security. Reference [52] explores the employment of the decision tree (DT) method in safety classification and the analysis of accidents at railway stations to predict the traits of passengers affected by accidents. In [56], Wayside Train Monitoring Systems (WTMS) are introduced, which use pattern recognition for defect detection in uncontrolled environments. The authors in [88]

TABLE I

INTERSECTION BETWEEN RAILWAY SUBDOMAINS AND AI RESEARCH FIELDS

	Expert systems	Data mining	Pattern recognition	Adversarial search
Maintenance and inspection	Y: visual inspection [43] fault diagnosis [44]	P: maintenance planning [45] defect prediction [46]	Y: defect prediction [47] failure prediction [48] defect detection [49]	P: maintenance planning [50]
Safety and security	Y: risk assessment [51]	Y: accident prediction [52], [53]	Y: defect detection [49]	P: risk assessment [54]
Autonomous driving and control	Y: intelligent train control [55]	P: intelligent train control [56]	U	Y: energy optimization [57]
Traffic planning and management	Y: train rescheduling [58] train timetabling [59]	Y: performance assessment [60] delay pattern recognition [61] train dispatching [62]	Y: train rescheduling [63]	Y train timetabling [64]
Revenue management	U	P: revenue forecasting [65] RM system design [66]	U	P: RM simulation [67] pricing [68]
Transport policy	P: urban public transport decision making [69] strategy selection [70]	P: public transit analyses [71] decision making [72]	U	P: public transport policy making [73], [74]
Passenger mobility	P: flow management [75]	Y: flow prediction [76], [77]	U	Y: flow simulation [78] passenger planning [79]

TABLE II

INTERSECTION BETWEEN RAILWAY SUBDOMAINS AND AI TECHNIQUES (ALL RESULTS FOR LOGIC PROGRAMMING ARE "U", AND THEREFORE NOT INCLUDED IN THE TABLE)

	Evolutionary computing	Machine learning
Maintenance and inspection	P: defect prediction[80] failure prediction[81] defect detection [82]	Y: defect prediction[83] defect detection[84], [85]
Safety and security	Y: train protection[86], speed error reduction[87]	Y: accidents [53] disruptions [88]
Autonomous driving and control	Y: energy optimization [89] intelligent train control [90]	Y: intelligent train control[55]
Traffic planning and management	Y: train timetabling [91], [92]	Y: delay analysis[40], train rescheduling [93] train timetabling [63], [94], train shunting[95]
Revenue management	P: revenue simulation [96]	P: overall revenue management[97] inventory control and prediction[98]
Transport policy	P: energy network policy making [99]	U
Passenger mobility	P: demand forecasting [100]	Y: flow prediction [101], [102]

developed a prediction model for the railway disruption length using Bayesian Networks.

Among the AI applications, in [105], Natural Language Processing is used in determining accident causation by exploiting text analysis approaches. Investigation reports of railway accidents in the UK were reviewed and analysed, to reveal the presence of entities which are informative of causes and failures. The proposed method is able to assist risk and incident analysis experts to study causal relationship between causes and failures towards the overall safety in rail industry.

In [109], computer vision techniques are used for various types of security applications, including train stations. According to the authors, the challenge does not lie on acquiring surveillance data from video cameras, but for identifying what is valuable, what can be ignored, and what demands immediate attention.

3) Autonomous Driving and Control: In autonomous driving and control we recognised the use of evolutionary algorithms and reinforcement learning for optimal train control. Reference [89] proposed a method for energy optimisation of the train movement applying control based on genetic algorithms. The algorithm was tested based on a real subway line in Milan. Reference [55] presents two train control algorithms – an expert system and a reinforcement learning – to operate the train similar to an experienced driver with real-time data to reduce energy consumption whilst maintaining comfort level and punctuality.

4) Traffic Planning and Management: Traffic planning and management is another sub-domain where many AI research fields have been extensively used tackling traffic state prediction, timetabling and traffic rescheduling as well as some more strategic planning decisions like equipment layout using e.g. clustering, reinforcement learning and evolutionary algorithms.

In the 70s, the first expert systems for real-time train dispatching were developed [58]. In [59], expert systems are used for intelligent train operations. In [60], a data analytics approach is designed for train timetable performance measures, where automatic train supervision data is used.

TABLE III
INTERSECTION BETWEEN RAILWAY SUBDOMAINS AND AI APPLICATIONS

	Operational research and scheduling	NLP & speech recognition	Computer vision & image processing	Autonomous systems & robotics
Maintenance and inspection	Y: defect & fault detection[103]	P: defect detection[104], [105]	Y: defect detection[47] failure detection[48]	P: autonomous maintenance [106], [107]
Safety and security	U	Y: railway accidents[108]	Y: anomaly detection[109]	Y: railway accidents[110] anomaly detection[111]
Autonomous driving and control	Y: energy optimization [57], [112]	U	P: autonomous driving [113]	U
Traffic planning and management	P: ML-based timetabling and rescheduling [114]	P: overall management [115]	U	U
Revenue management	P: pricing [116] RM system design[117]	U	U	U
Transport policy	P: policy making [99]	P: tourist satisfaction analysis [118]	U	U
Passenger mobility	U	Y: passenger sentiment analysis [119]	U	U

To analyse train delay patterns, [61] applies data clustering techniques and [120] uses regressions and random forest techniques. Finally, [62] gives a comprehensive survey on the use of data-driven approaches for train dispatching management.

In [93], a scalable reinforcement learning algorithm is proposed for scheduling railway lines. The goal is to define track allocations and arrival/departure times for all trains of a line, provided with their initial positions, priority, dwell times, and running times, while minimising the total priority-weighted delay. Reference [63] solves the problem of optimising dispatching and rerouting in the Swiss railway network by deep reinforcement learning and pattern recognition, where the recorded data is variable over time and only contains a few valuable events. To overcome the deficiency of the lack of valuable data, they use the high computational power of modern GPUs to simulate millions of physically plausible scenarios. Artificial data are then used to train their algorithm. Similarly, reinforcement learning has been used for train scheduling [94] and shunting in yards [95].

Since most traffic planning and management problems are NP-hard, evolutionary algorithms are often used to get near-optimal solutions within reasonable time. In [92], an alternative mathematical model to tackle the timetabling problem is proposed and a Genetic Algorithm is used for solving the model in order to rapidly obtain near-optimal solutions. Computational experiments were conducted based on a German railway network. Reference [91] presents a heuristic model based on the concept of *Fixed Path + Genetic Algorithm*. The Fixed Path model assumes that the path of the trains is fixed for preparing the train schedule. The GA is used for selecting for each train the minimum-time path to arrive at the destination. Combined, they give a schedule minimising the travel time of each train while maximising capacity of the network. This paper also shows that rail traffic can be improved regarding the increase of timetable stability and maximizing capacity subject to safety constraints. More strategically, [87] combined a genetic algorithm, particle swarm optimisation algorithm, and Kalman filtering for determining the best locations of balises in order to minimise speed error of railway vehicles.

5) Passenger Mobility: Passenger mobility has received not as much research attention as in other subdomains, mostly for predicting passenger flows in railway and metro networks. Reference [77] also uses data mining to forecast railway passenger flows. A combination of methods such as data warehousing, data mining and neural networks are used. In particular, the result was applied to the Ticket Selling and Reserving System of Chinese Railways. In [101], artificial neural networks are used for forecasting passenger flows on metro lines. Artificial Neural Networks are trained by using simulated data from a dynamic loading of the line. The proposed method was tested on Line 1 of the Naples metro system in Italy. Computational experiments show that the proposed approach is able to forecast the flows on metro sections with satisfactory precision. Reference [102] proposes a deep learning based architecture for metro passenger flow prediction. This architecture is highly flexible and extendable, suitable for the integration and modelling of external environmental factors, temporal dependencies, spatial characteristics, and metro operational properties in short-term metro passenger flow prediction. It achieves a high prediction accuracy due to the ease of integrating multi-source data as evidenced by computational experiments. Differently, [119] used NLP to evaluate passenger satisfaction with the system operations by analysing the information extracted from the tweets from customers.

B. Potential Applications: Promising Research Directions

We identify some examples of potential applications of AI in railways as defined in Tables I-III. These are formed based on existing ones in similar (transport) domains.

1) Data Mining for Maintenance and Autonomous Driving: One of the essential challenges to be tackled is using automated data processing and analysis techniques for efficient exploration/understanding of new knowledge, from the huge amount of complex data structures. Approaches from e.g. manufacturing [45] could be translated to railway maintenance as well. Next to that, it becomes important to protect infrastructure condition monitoring data between maintenance operating companies. For example, to address it, [46] created an organisational architecture that integrates data produced in factories on their activities of reactive, predictive and preventive maintenance. The main idea would be to develop a decentralised predictive maintenance system based on data mining concepts. In addition, fast real-time/online data mining are prerequisite for online learning and autonomous driving. Therefore advanced collecting, combining and processing data from different sources (i.e. sensors, cameras) is a must to provide accurate information to the AI-based control system [56].

2) Evolutionary Computing for Maintenance and Defect Detection: Methods for finding an optimal set of parameters i.e. feature selection methods, would provide benefits to defect detection in railway maintenance such as signal fault, track inspection, and so on. Feature selection techniques are used to maximise discrimination: the selection method could use a genetic algorithm to optimise various parameters of the system. For example, [82] proposed a model for texture segmentation in wood manufacturing using Gabor filters to the analysis of texture and defect regions found on wooden boards. Also, possible applications are seen for using GA for preventive maintenance [80], [81]. These would lead to providing to focus on the most important characteristics while disregarding the others, and thus lead to smaller required datasets and hopefully simpler and more efficient AI models.

3) Autonomous Systems for Maintenance: Unmanned aerial vehicles like drones can be used for efficient and regular inspection of railway resources, including rail tracks, catenary and power system. For example, [107] presented using UAVs for plant inspection. In general, use of automated systems in maintenance tasks tends to provide additional support in automating operations leading to increased efficiency, productivity and safety [106].

4) Computer Vision for Automated Driving: Computer vision based on deep learning could become extremely useful for complex tasks of object detection (e.g. an obstacle on tracks) and semantic segmentation (e.g. distinguish between signals, signs, rails, and road crossings). Recently, the image recognition methods using deep learning proved to be far superior to the methods used prior to the appearance of deep learning in general object recognition competitions [113].

5) Machine Learning for Autonomous Driving: The concepts of ML for automated car driving are likely to be transferred from road to railways once the techniques in car driving are mature enough, e.g. [121]–[123]. ML may play a key role in this area but this is not as simple as out-of-the box deployment of strategies and models developed in related fields. Weston [128] argues that a system-centric approach not only allows us to meet the necessary requirements for real world deployment but also affords the machine learning community new opportunities for developing the next generation of intelligent algorithms.

6) Adversarial Search for Maintenance Scheduling: In maintenance scheduling, facility managers and staff must deal with many daily maintenance requests despite various limitations, such as limited budgets and staff, which can cause delays in responding to some maintenance requests. Maintenance work is scheduled according to various priorities. For example, in [50] facility managers considered the impact of each problem in terms of system failure and safety, and proposed a framework to incorporate the interplay between energy efficiency and occupant satisfaction. This can be extended to the railway context in order to optimise maintenance planning and reduce impacts on traffic operations.

7) Adversarial Search for Security: For security applications in railway stations and terminals, new approaches combining traditional security risk management methodologies with agent-based modelling and Monte Carlo simulation can be used for risk assessment, and risk mitigation. Similar applications for airports security [54] may represent a promising basis. In addition, there might be potential to extend this approach to important station shunting yards, depots, signalling and control centres. Lastly, applying this method to on-board trains will also further improve the security of passengers.

8) Operations Research for Traffic Planning and Management: Most typical traffic management problems can be modelled as combinatorial optimisation problems, which are traditionally solved by classical optimisation approaches such as branch-and-bound or heuristic-based methods. Recently, there have been considerable advances in solving combinatorial optimisation problems by mathematical programming and machine learning [114]. This implies that as there is great potential in solving railway planning and scheduling problems using AI given the fast-growing research interests in the theoretical optimisation community.

9) NLP for Railway Transport: NLP has a significant potential in railways to process unstructured or semi-structured documents/records, such as maintenance and disruption reports, social networks. As such, it can find applications in subdomains such as maintenance, traffic planning and management and transport policy. Maintenance records can be successfully processed by NLP to determine the most critical components, which can further lead to determining optimised maintenance strategies [104]. For example, [105] used NLP to detect duplicate defect reports at Sony Ericsson Mobile Communications. For railway traffic management, NLP could be investigated for design, implementation and usage of ontologies and natural language in order to bridge the gap between a "machine readable representation of data" and a "user friendly presentation of data" [115]. The adoption of ontologies could enable the management of Centralized Traffic Control (CTC) logic and the improvement of the user interface through the exploitation of natural language queries. Also, it could create automatically a human readable description of the ontology structure and of its instances that can describe "informally" the structure of the railway CTC and its rules, without losing any coherence and information. For transport policy, the potential of applying big data and text mining technologies from social media could support policy makers in transport analysis and policy making, including NLP as a powerful tool for text mining and analysis [118]. The article is about generic transport policy making, and there is no reason that railways, as an important sector of transport, would be excluded from this potential direction.

10) AI for Revenue Management: Future revenue management systems for railway transport can use AI for ticket pricing, seat and discount allocation, and overbooking [116], defining competitive pricing of offered services between multiple operators [68], and developing adaptive RM systems that could automatically learn by directly interacting with customers [98], [117]. Revenue management systems for railway transport share certain features with other RM systems while having their own uniqueness. As the applications of AI in RM systems in other areas becomes mature such as airline [97], there is a possibility that they can be transferred to the railway sector, since the differences between the RM systems in different fields should not be significant enough to challenge such a transferring process.

11) AI for Transport Policy: Using AI for policy making is rather at its early stages of development, but certain promising applications of expert systems, optimisation techniques, adversarial search and data mining could be envisioned [124]. Policy planning can often be modelled as a combinatorial problem [99], and using an AI-based techniques could provide the best planning actions. Also, game-theoretic approaches combined with ML or EC could be used for negotiating and/or auctions when competing for certain activities, where each participant is typically seeking to maximise his/her utility [73], [125]. In railways, these can be used for bidding of multiple operators to award a concession for traffic services or maintenance works. Alternatively, it can be used to describe the dynamic interactions between the government, public transport company, and travellers when deciding to open a new line or a station [74]. Expert systems like the ones in public transport for deciding on preferable technologies could be useful for rails as well, for e.g. developing mobility management strategies [69], [70]. By having the increased availability of smart cards and vehicle movement data also comes to the new need for applications of more advanced mining methods to learn patterns and preferences required for policy management, and also for improving mobility and transport planning [71].

12) Evolutionary Computing for Passenger Mobility: Transport predictions including passenger and freight demand, are expected to become be increasingly important as the system is likely to get more dynamic and data-driven. To do achieve that, apart from ML techniques, genetic algorithms could be considered as well. For example, [100] presented a forecasting tool for predicting airline passenger demand using GA, and demonstrated its more accurate, reliable, and greater predictive capabilities as compared to the traditional statistical models.

C. Uncertain Applications: Challenging Research Directions

The topics marked with Uncertain (U) in Tables I-III represent more adventurous, i.e. challenging to reach, research opportunities in the future that seem to be not recognised yet by the research community and practitioners at the moment. We recognise that some of the current U intersections could provide promising research directions at the crossings of, for example, traffic management & computer vision/speech recognition, autonomous driving and logic programming, security and operations research, transport policy and machine learning. In particular, we determine the following directions:

1) **Trustworthy AI for automated driving and safety**. Developing regulations and standardised certification processes are required to precisely quantify the trustworthiness of an AI-based system, and thus its safety and dependable characteristics to be able providing e.g. safe autonomous train operation, which is of utmost importance for system performance. Therefore, it is advised to exploit Explainable AI (XAI) approaches to make these future systems more understandable.
2) **Computer vision for passenger mobility**. Computer vision can provide advanced motion tracking both at stations and onboard including passenger crowd characterization and emotion recognition to monitor passenger satisfaction, including driverless vehicles, and provide personalised trip advisors and experience, among others to visually impaired persons.
3) **Computer vision for Traffic planning and management**. Visual support tools could be used to help dispatchers with more user friendly interfaces and provide the right information and at the right time.
4) **Logic programming for human-based decision making**. logic programming could be used to develop decision support tools based on experienced practitioners, e.g. planners, dispatchers, and maintenance workers.
5) **Operations research for safety and policy**. Operations research-based models can be used to tackle new (cyber-) security challenges. Also, during pandemics, such as Covid-19, distancing between passengers, i.e. seat allocation, could be optimised using OR-based models in order to increase the passenger health safety on board. In addition, the increased awareness of AI usability among strategical decision/policy makers can be expected, and new applications could arise in transport policy.

Finally, some of the Us tend to be trivial for lack of applications (as no connections can be defined) such as revenue management & pattern recognition, or autonomous systems and robotics & revenue management and transport policy. Thus, today, it is rather difficult to envision possible related applications in the future. However, further developments of AI and railway technologies could indeed generate new potential uses of AI in these subdomains as well.

VII. Conclusion

This paper defined a taxonomy for AI in railways. It gives a comprehensive definition of AI that is relevant and highly useful for railway academics and practitioners. To address the complex world of AI and bring it towards railways, we classify AI into three main classes: research fields, techniques and applications, and explain their main characteristics. Further, differently from earlier research, this paper covers railway systems holistically including maintenance, safety and security, autonomous driving, transport planning, revenue management, transport policy and passenger mobility. As such it makes a first step in recognising AI in the railway domain.

We mapped the current railway research to the AI taxonomy and recognised that maintenance has generated the most AI-related research, where pattern recognition, machine learning, computer vision and image processing are the most frequently used AI areas in research fields, techniques and applications respectively. Other rail subdomains received attentions from almost none to medially found papers. Notably, safety and security share similar AI categories to those found in maintenance and inspection, possibly because many safety and security problems inherently link with maintenance and inspection. The use of AI in Autonomous driving & control and traffic planning and management has been more popular than it used to be. In particular, the latter has got all Ys in AI research fields. We also notice that operations research, a powerful traditional tool in railway operations, heavily intersects with planning and management. Revenue management, Transport policy and Passenger mobility are the least populated subdomains in terms of Ys, which could mean either there is great potential in applying AI to some of them, or some are simply not appropriate areas for introducing AI at the moment. It is also worth remarking that logic programming has never been used in any rail subdomains. Finally, ethics in AI and explainable AI still remain to gain attraction in all railway subdomains.

In addition, we determined some promising research directions. First, some relevant AI applications exist in other domains, similar to railways, however, such problems have not been addressed in railways yet, such as AI-based advanced autonomous driving, and safety and security applications. Second, we also determined topics that have no AI research in rail nor in other related domains. Some examples are revenue management and transport policy. This makes them even more suitable for more fundamental contributions to railway research in future. Third, AI-powered railway can, on one side benefit from other smart domains such as smart cities and ITS, and on the other support them towards increasing their "smartness" through machine learning and other AI techniques, which would lead to future data-driven and flexible transport systems. Overall, we recognise that AI research is at its dawn in the railway domain and we expect a growing interest in existing problems using new techniques as well as finding new problems to be solved by new AI techniques. This all together makes the railway domain a fruitful future playing field for new AI advances.

Acknowledgment

The JU receives support from the European Union's Horizon 2020 Research and Innovation Program and the Shift2Rail JU members other than the Union.

References

[1] *Artificial Intelligence in the Real World: The Business Case Takes Shape*, The Economist Intelligence Unit, London, U.K., 2016.

[2] M. Trosino, J. Cunningham, and A. Shaw, "Automated track inspection vehicle and method," U.S. Patent 6 356 299, Mar. 16, 2002.

[3] X. Gibert, V. M. Patel, and R. Chellappa, "Deep multitask learning for railway track inspection," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 1, pp. 153–164, Jan. 2017.

[4] J. McCarthy, "What is artificial intelligence?" Dept. Comput. Sci., Stanford Univ., Stanford, CA, USA, Tech. Rep., 1998.

[5] A. Agrawal, J. Gans, and A. Goldfarb, *What to Expect From Artificial Intelligence*. Cambridge, MA, USA: MIT Sloan Management Review, 2017.

[6] C. Chandra and A. Tumanyan, "Supply chain system taxonomy: A framework and methodology," *Hum. Syst. Manage.*, vol. 24, no. 4, pp. 245–258, Nov. 2005.

[7] S. Wilke and A. Majumdar, "Critical factors underlying airport surface accidents and incidents: A holistic taxonomy," *J. Airport Manage.*, vol. 6, no. 2, pp. 170–190, 2012.

[8] N. Grant, T. Cadden, R. McIvor, and P. Humphreys, "A taxonomy of manufacturing strategies in manufacturing companies in Ireland," *J. Manuf. Technol. Manage.*, vol. 24, no. 4, pp. 488–510, Apr. 2013.

[9] M. Kyriakidis, A. Majumdar, G. Grote, and W. Y. Ochieng, "Development and assessment of taxonomy for performance-shaping factors for railway operations," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2289, no. 1, pp. 145–153, Jan. 2012.

[10] P. Lopez Diez, I. Gabilondo, E. Alarcon, and F. Moll, "Mechanical energy harvesting taxonomy for industrial environments: Application to the railway industry," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 7, pp. 2696–2706, Jul. 2020.

[11] S. Tang and H. K. Lo, "Taxonomy of public private partnership on mass railway transit development—A benchmark with Hong Kong experience," *Transp. Syst., Eng. Manage.*, pp. 665–674, Dec. 2007. [Online]. Available: https://repository.ust.hk/ir/Record/1783.1-39558

[12] W. H. Gibson, E. Megaw, M. S. Young, and E. Lowe, "A taxonomy of human communication errors and application to railway track maintenance," *Cognition, Technol. Work*, vol. 8, no. 1, p. 57, 2006.

[13] K. Sheth, K. Patel, H. Shah, S. Tanwar, R. Gupta, and N. Kumar, "A taxonomy of AI techniques for 6G communication networks," *Comput. Commun.*, vol. 161, pp. 279–303, Sep. 2020.

[14] J. S. Angarita-Zapata, A. D. Masegosa, and I. Triguero, "A taxonomy of traffic forecasting regression problems from a supervised learning perspective," *IEEE Access*, vol. 7, pp. 68185–68205, 2019.

[15] J. Suaboot *et al.*, "A taxonomy of supervised learning for IDSs in SCADA environments," *ACM Comput. Surv.*, vol. 53, no. 2, pp. 1–37, Jul. 2020.

[16] J. Del Ser, E. Osaba, J. J. Sanchez-Medina, and I. Fister, "Bioinspired computational intelligence and transportation systems: A long road ahead," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 2, pp. 466–495, Mar. 2019.

[17] J. Xie, J. Huang, C. Zeng, S.-H. Jiang, and N. Podlich, "Systematic literature review on data-driven models for predictive maintenance of railway track: Implications in geotechnical engineering," *Geoscience*, vol. 10, no. 11, pp. 1–24, 2020.

[18] M. Chenariyan Nakhaee, D. Hiemstra, M. Stoelinga, and M. Van Noort, "The recent applications of machine learning in rail track maintenance: A survey," in *Reliability, Safety, and Security of Railway Systems. Modelling, Analysis, Verification, and Certification*, S. Collart-Dutilleul, T. Lecomte, and A. Romanovsky, Eds. Cham, Switzerland: Springer, 2019, pp. 91–105.

[19] A. Przegalinska. (2019). *State of the Art and Future of Artificial Intelligence*. [Online]. Available: https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai

[20] A. M. Turing, "Computing machinery and intelligence," in *Parsing Turing Test*. Dordrecht, The Netherlands: Springer, 2009, pp. 23–65.

[21] *Communication From the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions*, European Commission, Brussels, Belgium, 2018.

[22] A. Annoni *et al.*, "Artificial intelligence: A European perspective," Joint Res. Centre, Seville, Spain, 2018. [Online]. Available: https://repository.ust.hk/ir/Record/1783.1-39558

[23] B. Copeland. (2019) *Artificial Intelligence*. [Online]. Available: https://www.britannica.com/technology/artificial-intelligence

[24] C. Di Meo, M. Di Vaio, F. Flammini, R. Nardone, S. Santini, and V. Vittorini, "ERTMS/ETCS virtual coupling: Proof of concept and numerical analysis," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 6, pp. 2545–2556, Jun. 2020.

[25] K. Kuru and D. Ansell, "Tcitysmartf: A comprehensive systematic framework for transforming cities into smart cities," *IEEE Access*, vol. 8, pp. 18615–18644, 2020.

[26] B. Jan., H. Farman, M. Khan, M. Talha, and I. U. Din, "Designing a smart transportation system: An Internet of Things and big data approach," *IEEE Wireless Commun.*, vol. 26, no. 4, pp. 73–79, Aug. 2019.

[27] F. Zantalis, G. Koulouras, S. Karabetsos, and D. Kandris, "A review of machine learning and IoT in smart transportation," *Future Internet*, vol. 11, no. 4, p. 94, Apr. 2019.

[28] C. Larman, *Applying UML and Patterns: An Introduction to Object Oriented Analysis and Design and Interative Development*. London, U.K.: Pearson, 2012.

[29] RAILS Project. (2020). *Deliverable 1.1 Definition of a Reference Taxonomy of AI in Railways*. [Online]. Available: https://rails-project.eu/wp-content/uploads/sites/73/2020/08/RAILS_D11_v25.pdf

[30] S. K. Pal and P. Mitra, *Pattern Recognition Algorithms for Data Mining*. Boca Raton, FL, USA: CRC Press, 2004.

[31] J. Han, J. Pei, and M. Kamber, *Data Mining: Concepts and Techniques*. Amsterdam, The Netherlands: Elsevier, 2011.

[32] *Ethics Guidelines for Trustworthy AI*, HLEG, EU, Brussels, Belgium, 2019. [Online]. Available: https://op.europa.eu/en/publication-detail/-/publication/d3988569-0434-11ea-8c1f-01aa75ed71a1

[33] R. Hamon, H. Junklewitz, and I. Sanchez, *Robustness and Explainability of Artificial Intelligence*. Luxembourg, U.K.: Office of the European Union, 2020.

[34] A. Barredo Arrieta *et al.*, "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Inf. Fusion*, vol. 58, pp. 82–115, Jun. 2020.

[35] M. Niestadt, A. Debyser, D. Scordamaglia, and M. Pape, "Artificial intelligence in transport: Current and future developments, opportunities and challenges," Eur. Parliamentary Res. Service, Eur. Parliament, Brussels, Belgium, Tech. Rep., 2019. [Online]. Available: https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/635609/EPRS_BRI(2019)635609_EN.pdf

[36] B. W. Smith, *The Oxford Handbook of Ethics of AI*. Oxford, U.K.: Oxford Univ. Press, 2020.

[37] H. Etienne, "When AI ethics Goes astray: A case study of autonomous vehicles," *Social Sci. Comput. Rev.*, vol. 2020, Feb. 2020, Art. no. 089443932090650.

[38] J. Morley *et al.*, "The ethics of AI in health care: A mapping review," *Social Sci. Med.*, vol. 260, Sep. 2020, Art. no. 113172.

[39] A. Winfield, "Ethical standards in robotics and AI," *Nature Electron.*, vol. 2, no. 2, pp. 46–48, Feb. 2019.

[40] D. Rößler, J. Reisch, F. Hauck, and N. Kliewer, "Discerning primary and secondary delays in railway networks using explainable AI," *Transp. Res. Proc.*, vol. 52, pp. 171–178, 2021.

[41] K. Gade, S. C. Geyik, K. Kenthapadi, V. Mithal, and A. Taly, "Explainable AI in industry," in *Proc. 25th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Jul. 2019, pp. 3203–3204.

[42] N. Duckworth, "AI in supply chain: Six barriers to seeing results," Supply Chain Brain, 2019. [Online]. Available: https://www.supplychainbrain.com/blogs/1-think-tank/post/30051-six-barriers-to-getting-results-with-ai-in-supply-chain-management

[43] S. Liu, Q. Wang, and Y. Luo, "A review of applications of visual inspection technology based on image processing in the railway industry," *Transp. Saf. Environ.*, vol. 1, no. 3, pp. 185–204, Dec. 2019.

[44] Y. Zang, W. Shangguan, B. Cai, H. Wang, and M. G. Pecht, "Methods for fault diagnosis of high-speed railways: A review," *Proc. Inst. Mech. Eng., O, J. Risk Rel.*, vol. 233, no. 5, pp. 908–922, Oct. 2019.

[45] B.-H. Li, B.-C. Hou, W.-T. Yu, X.-B. Lu, and C.-W. Yang, "Applications of artificial intelligence in intelligent manufacturing: A review," *Frontiers Inf. Technol. Electron. Eng.*, vol. 18, no. 1, pp. 86–96, 2017.

[46] P. Bastos, R. Lopes, L. Pires, and T. Pedrosa, "Maintenance behaviour-based prediction system using data mining," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage.*, Dec. 2009, pp. 2487–2491.

[47] NOS. (2017). *Prorail Kan Wisselstoringen Voorspellen*. [Online]. Available: https://nos.nl/artikel/2176395-prorail-kan-wisselstoringen-voorspellen.html

[48] SpoorPro. (2019) *Experiment Zelfrijdende Passagierstrein Geslaagd*. [Online]. Available: https://www.spoorpro.nl/materieel/2019/03/15/experiment-met-zelfrijdende-passagierstrein-geslaagd/

[49] G. Di Leo, R. Lengu, N. Mazzino, and A. Paolillo, "Pattern recognition for defect detection in uncontrolled environment railway applications," in *Image Analysis Processing*, A. Petrosino, Ed. Berlin, Germany: Springer, 2013, pp. 753–757.

[50] Y. Cao, T. Wang, and X. Song, "An energy-aware, agent-based maintenance-scheduling framework to improve occupant satisfaction," *Autom. Construct.*, vol. 60, pp. 49–57, Dec. 2015.

[51] M. Gul and E. Celik, "Fuzzy rule-based Fine–Kinney risk assessment approach for rail transportation systems," *Hum. Ecol. Risk Assessment, Int. J.*, vol. 24, no. 7, pp. 1786–1812, Oct. 2018.

[52] H. Alawad, S. Kaewunruen, and M. An, "Learning from accidents: Machine learning for safety at railway stations," *IEEE Access*, vol. 8, pp. 633–648, 2020.

[53] S. Shalini and A. A. Narasimham, "A review on rail accidents and predictions using data mining techniques," *Int. J. Res.*, vol. 4, pp. 2094–2098, 2017.

[54] S. Janssen, A. Sharpanskykh, and R. Curran, "AbSRiM: An agent-based security risk management approach for airport operations," *Risk Anal.*, vol. 39, no. 7, pp. 1582–1596, Jul. 2019.

[55] J. Yin, S. Su, J. Xun, T. Tang, and R. Liu, "Data-driven approaches for modeling train control models: Comparison and case studies," *ISA Trans.*, vol. 98, pp. 349–363, Mar. 2020.

[56] M. O'Brien, K. Neubauer, J. Van Brummelen, and H. Najjaran, "Analysis of driving data for autonomous vehicle applications," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Dec. 2017, pp. 3677–3682.

[57] H. Ye and R. Liu, "Nonlinear programming methods based on closed-form expressions for optimal train control," *Transp. Res. C, Emerg. Technol.*, vol. 82, pp. 102–123, Sep. 2017.

[58] H. Schaefer and S. Pferdmenges, "An expert system for real-time train dispatching," *WIT Trans. Built Environ.*, vol. 7, pp. 27–34, Dec. 1970.

[59] J. Yin, D. Chen, and L. Li, "Intelligent train operation algorithms for subway by expert system and reinforcement learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 6, pp. 2561–2571, Dec. 2014.

[60] F. Liu, R. Xu, W. Fan, and Z. Jiang, "Data analytics approach for train timetable performance measures using automatic train supervision data," *IET Intell. Transp. Syst.*, vol. 12, no. 7, pp. 568–577, Sep. 2018.

[61] F. Cerreto, B. F. Nielsen, O. A. Nielsen, and S. S. Harrod, "Application of data clustering to railway delay pattern recognition," *J. Adv. Transp.*, vol. 2018, pp. 1–18, 2018.

[62] C. Wen *et al.*, "Train dispatching management with data-driven approaches: A comprehensive review and appraisal," *IEEE Access*, vol. 7, pp. 114547–114571, 2019.

[63] E. Nygren, A. Egli, D. Abels, L. Jöckel, and L. Rothen, "Reinforcement learning for railway scheduling: Overcoming data sparseness through simulations," in *Performance Computing*. San Jose, CA, USA: GTC Europe, 2017.

[64] V. Fragnelli and S. Sanguineti, "A game theoretic model for re-optimizing a railway timetable," *Eur. Transp. Res. Rev.*, vol. 6, no. 2, pp. 113–125, Jun. 2014.

[65] Z. Schwartz, T. Webb, and L. Koupriouchina, "Enhancing the accuracy of revenue management system forecasts: The impact of machine and human learning on the effectiveness of hotel occupancy forecast combinations across multiple forecasting horizons," *Tourism Econ.*, vol. 27, no. 2, pp. 273–291, 2019.

[66] C. Bahadir and A. Karahoca, "Airline revenue management via data mining," *Global J. Inf. Technol., Emerg. Technol.*, vol. 7, no. 3, pp. 128–148, Dec. 2017.

[67] C. Cleophas, "Multi-agent modelling for revenue management," *J. Revenue Pricing Manage.*, vol. 11, no. 2, pp. 240–242, Mar. 2012.

[68] K. Isler and H. Imhof, "A game theoretic model for airline revenue management and competitive pricing," *J. Revenue Pricing Manage.*, vol. 7, no. 4, pp. 384–396, Dec. 2008.

[69] R. Mackett and M. Edwards, "An expert system to advise on urban public transport technologies," *Comput., Environ. Urban Syst.*, vol. 20, nos. 4–5, pp. 261–273, Jul. 1996.

[70] B. S. Salleh, R. A. O. K. Rahmat, and A. Ismail, "Expert system on selection of mobility management strategies towards implementing active transport," *Proc.-Social Behav. Sci.*, vol. 195, pp. 2896–2904, Jul. 2015.

[71] T. F. Welch and A. Widita, "Big data in public transportation: A review of sources and methods," *Transp. Rev.*, vol. 39, no. 6, pp. 795–818, Nov. 2019.

[72] Y. Wang and Z. Zeng, *Data-Driven Solutions to Transportation Problems*. Amsterdam, The Netherlands: Elsevier, 2018.

[73] A. Roumboutsos and S. Kapros, "A game theory approach to urban public transport integration policy," *Transp. Policy*, vol. 15, no. 4, pp. 209–215, Jul. 2008.

[74] W. Zhu, M. Chen, D. Wang, and D. Ma, "Policy-combination oriented optimization for public transportation based on the game theory," *Math. Problems Eng.*, vol. 2018, pp. 1–14, Jul. 2018.

[75] L. Weigang, C. J. P. Alves, and N. Omar, "An expert system for air traffic flow management," *J. Adv. Transp.*, vol. 31, no. 3, pp. 343–361, Jun. 1997.

[76] W. Xu, Y. Qin, and H. Huang, "A new method of railway passenger flow forecasting based on spatio-temporal data mining," in *Proc. 7th Int. Conf. Intell. Transp. Syst.*, 2004, pp. 402–405.

[77] D. Zheng, Y. Wang, P. Z. Tang, and Y. P. Wu, "Application of data mining in the forecasting of railway passenger flow," *Adv. Mater. Res.*, vols. 834–836, pp. 958–961, Oct. 2013.

[78] O. Makinde, D. Neagu, and M. Gheorghe, "Agent based micro-simulation of a passenger rail system using customer survey data and an activity based approach," in *Proc. Workshop Comput. Intell.* Cham, Switzerland: Springer, 2018, pp. 123–137.

[79] X. Jiang, X. Zhang, W. Lu, L. Zhang, and X. Chen, "Competition between high-speed rail and airline based on game theory," *Math. Problems Eng.*, vol. 2017, pp. 1–9, 2017.

[80] I. Maatouk, I. Jarkass, E. Chätelet, and N. Chebbo, "Preventive maintenance optimization and comparison of genetic algorithm models in a Series–Parallel multi-state system," *J. Intell. Syst.*, vol. 28, no. 2, pp. 219–230, Apr. 2019.

[81] S. Martorell, S. Carlos, J. F. Villanueva, and A. Sánchez, "Genetic algorithm applications in surveillance and maintenance optimization," in *Computational Intelligence in Reliability Engineering*. Berlin, Germany: Springer, 2007, pp. 63–99.

[82] W. Polzleitner, "Defect detection on wooden surface using Gabor filters with evolutionary algorithm design," in *Proc. Int. Joint Conf. Neural Netw.*, vol. 1, 2001, pp. 750–755.

[83] W. Sammouri, E. Come, L. Oukhellou, P. Aknin, and C.-E. Fonlladosa, "Pattern recognition approach for the prediction of infrequent target events in floating train data sequences within a predictive maintenance framework," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 918–923.

[84] X. Wei, Z. Yang, Y. Liu, D. Wei, L. Jia, and Y. Li, "Railway track fastener defect detection based on image processing and deep learning techniques: A comparative study," *Eng. Appl. Artif. Intell.*, vol. 80, pp. 66–81, Apr. 2019.

[85] G. Krummenacher, C. S. Ong, S. Koller, S. Kobayashi, and J. M. Buhmann, "Wheel defect detection with machine learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 4, pp. 1176–1187, Apr. 2018.

[86] L. Xiao, Z. Ya-Dong, and G. Jin, "Application of genetic algorithm in automatic train protection," in *Proc. 5th Int. Conf. Intell. Hum.-Mach. Syst. Cybern. (IHMSC)*, vol. 2, Aug. 2013, pp. 152–154.

[87] M. A. Sandidzadeh, A. Heydari, and A. Khodadadi, "Genetic algorithm and particle swarm optimization algorithm for speed error reduction in railway signaling systems," *Int. J. Adapt. Control Signal Process.*, vol. 27, no. 6, pp. 478–487, Jun. 2013.

[88] A. A. Zilko, D. Kurowicka, and R. M. Goverde, "Modeling railway disruption lengths with copula Bayesian networks," *Transp. Res. C, Emerg. Technol.*, vol. 68, pp. 350–368, Jul. 2016.

[89] M. Brenna, F. Foiadelli, and M. Longo, "Application of genetic algorithms for driverless subway train energy optimization," *Int. J. Veh. Technol.*, vol. 2016, pp. 1–14, Feb. 2016.

[90] W. C. Carre no, "Efficient driving of CBTC ATO operated trains," Ph.D. dissertation, Escuela Tecnica Superior de Ingenieria, Univ. Pontificia Comillas, KTH Roy. Inst. Technol., Stockholm, Sweden, 2017.

[91] R. Barman *et al.*, "Automated train scheduling system using genetic algorithm," in *Proc. Int. Symp. Adv. Comput. Commun. (ISACC)*, 2015, pp. 28–33.

[92] D. Arenas, R. Chevrier, S. Hanafi, and J. Rodriguez, "Solving the Train Timetabling Problem, a mathematical model and a genetic algorithm solution approach," in *Proc. 6th Int. Conf. Railway Oper. Modeling Anal.*, Tokyo, Japan, Mar. 2015, pp. 1–13. [Online]. Available: https://hal.archives-ouvertes.fr/hal-01338609

[93] D. Šemrov, R. Marsetic, M. Žura, L. Todorovski, and A. Srdic, "Reinforcement learning approach for train rescheduling on a single-track railway," *Transp. Res. B, Methodol.*, vol. 86, pp. 250–267, Apr. 2016.

[94] H. Khadilkar, "A scalable reinforcement learning algorithm for scheduling railway lines," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 2, pp. 727–736, Feb. 2019.

[95] E. Peer, V. Menkovski, Y. Zhang, and W.-J. Lee, "Shunting trains with deep reinforcement learning," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2018, pp. 3063–3068.

[96] S. Vock, S. Enz, and C. Cleophas, "Genetic algorithms for calibrating airline revenue management simulations," in *Proc. Winter Simul. Conf.*, Dec. 2014, pp. 264–275.

[97] J.-M. Sauvage. (2019) *How Artificial Intelligence is Transforming Revenue Management for Airlines*. [Online]. Available: https://amadeus.com/en/insights/blog/airline-ai-ml-revenue-management

[98] S. Arbab Mohd Shihab, C. Logemann, D.-G. Thomas, and P. Wei, "Autonomous airline revenue management: A deep reinforcement learning approach to seat inventory control and overbooking," 2019, *arXiv:1902.06824*.

[99] M. Gavanelli, F. Riguzzi, M. Milano, and P. Cagnoli, "Constraint and optimization techniques for supporting policy making," in *Computational Intelligent Data Analysis for Sustainable Development, Data Mining and Knowledge Discovery Series*, T. Yu, N. Chawla, and S. Simoff, Eds. Boca Raton, FL, USA: CRC Press, 2013, ch. 12.

[100] P. Srisaeng, G. Baxter, S. Richardson, and G. Wild, "A forecasting tool for predicting Australia's domestic airline passenger demand using a genetic algorithm," *J. Aerosp. Technol. Manage.*, vol. 7, no. 4, pp. 476–489, Nov. 2015.

[101] M. Gallo, G. De Luca, L. D'Acierno, and M. Botte, "Artificial neural networks for forecasting passenger flows on metro lines," *Sensors*, vol. 19, no. 15, p. 3424, Aug. 2019.

[102] Y. Liu, Z. Liu, and R. Jia, "DeepPF: A deep learning based architecture for metro passenger flow prediction," *Transp. Res. C, Emerg. Technol.*, vol. 101, pp. 18–34, Apr. 2019.

[103] G. Park, W. Y. Yun, Y. Han, and J. Kim, "Optimal preventive maintenance intervals of a rolling stock system," in *Proc. Int. Conf. Qual., Rel., Risk, Maintenance, Saf. Eng.*, 2011, pp. 427–430.

[104] T. Edwards, A. Bayoumi, and M. L. Eisner, "Internet of Things—A complete solution for aviation's predictive maintenance," in *Advanced Technologies for Sustainable Systems*. Cham, Switzerland: Springer, 2017, pp. 167–177.

[105] P. Runeson, M. Alexandersson, and O. Nyholm, "Detection of duplicate defect reports using natural language processing," in *Proc. 29th Int. Conf. Softw. Eng. (ICSE)*, May 2007, pp. 499–510.

[106] T. Gamer, M. Hoernicke, B. Kloepper, R. Bauer, and A. J. Isaksson, "The autonomous industrial plant–future of process engineering, operations and maintenance," *J. Process. Control*, vol. 88, pp. 101–110, Apr. 2020.

[107] P. B. Quater, F. Grimaccia, S. Leva, M. Mussetta, and M. Aghaei, "Light unmanned aerial vehicles (UAVs) for cooperative inspection of PV plants," *IEEE J. Photovolt.*, vol. 4, no. 4, pp. 1107–1113, Jul. 2014.

[108] K. N. Syeda, S. N. Shirazi, S. A. A. Naqvi, H. J. Parkinson, and G. Bamford, "Big data and natural language processing for analysing railway safety: Analysis of railway incident reports," in *Human Performance Technology: Concepts, Methodologies, Tools, and Applications*. Hershey, PA, USA: IGI Global, 2019, pp. 781–809.

[109] S. Sasi, "Security applications using computer vision," in *Robotic Vision: Technologies for Machine Learning and Vision Applications*. Hershey, PA, USA: IGI Global, 2013, pp. 60–77.

[110] M. Sturari, M. Paolanti, E. Frontoni, A. Mancini, and P. Zingaretti, "Robotic platform for deep change detection for rail safety and security," in *Proc. Eur. Conf. Mobile Robots (ECMR)*, Sep. 2017, pp. 1–6.

[111] H. Grabe. (2019). *Autonomous Systems for Condition Monitoring of Railway Infrastructure*. [Online]. Available: https://www.railways.africa/coffee-with-the-editor/autonomous-systems-for-condition-monitoring-of-railway-infrastructure/

[112] W. Carvajal-Carreño, A. P. Cucala, and A. Fernández-Cardador, "Optimal design of energy-efficient ATO CBTC driving for metro lines based on NSGA-II with fuzzy parameters," *Eng. Appl. Artif. Intell.*, vol. 36, pp. 164–177, Nov. 2014.

[113] H. Fujiyoshi, T. Hirakawa, and T. Yamashita, "Deep learning-based image recognition for autonomous driving," *IATSS Res.*, vol. 43, no. 4, pp. 244–252, Dec. 2019.

[114] Y. Bengio, A. Lodi, and A. Prouvost, "Machine learning for combinatorial optimization: A methodological tour d'horizon," *Eur. J. Oper. Res.*, vol. 290, no. 2, pp. 405–421, Apr. 2021.

[115] D. Briola, R. Caccia, M. Bozzano, and A. Locoro, "Ontologica: Exploiting ontologies and natural language for railway management. Design, implementation and usage examples," *Int. J. Knowl.-Based Intell. Eng. Syst.*, vol. 17, no. 1, pp. 3–15, Jan. 2013.

[116] A. Gosavii, N. Bandla, and T. K. Das, "A reinforcement learning approach to a single leg airline revenue management problem with multiple fare classes and overbooking," *IIE Trans.*, vol. 34, no. 9, pp. 729–742, Sep. 2002.

[117] N. Bondoux, A. Q. Nguyen, T. Fiig, and R. Acuna-Agost, "Reinforcement learning applied to airline revenue management," *J. Revenue Pricing Manage.*, vol. 19, pp. 332–348, Jan. 2020.

[118] A. Serna and S. Gasparovic, "Transport analysis approach based on big data and text mining analysis from social media," *Transp. Res. Proc.*, vol. 33, pp. 291–298, 2018.

[119] M. B. Myneni and R. Dandamudi, "Harvesting railway passenger opinions on multi themes by using social graph clustering," *J. Rail Transp. Planning Manage.*, vol. 13, May 2020, Art. no. 100151.

[120] P. Kecman and R. M. Goverde, "Predictive modelling of running and dwell times in railway traffic," *Transportation*, vol. 7, no. 3, pp. 295–319, 2015.

[121] A. E. Sallab, M. Abdou, E. Perot, and S. Yogamani, "Deep reinforcement learning framework for autonomous driving," *Electron. Imag.*, vol. 2017, no. 19, pp. 70–76, 2017.

[122] S. Kuutti, R. Bowden, Y. Jin, P. Barber, and S. Fallah, "A survey of deep learning applications to autonomous vehicle control," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 2, pp. 712–733, Feb. 2020.

[123] M. Vitelli and A. Nayebi, "CARMA: A deep reinforcement learning approach to autonomous driving," Stanford Univ., Stanford, CA, USA, Tech. Rep., 2016.

[124] M. Milano, B. O'Sullivan, and M. Gavanelli, "Sustainable policy making: A strategic challenge for artificial intelligence," *AI Mag.*, vol. 35, no. 3, pp. 22–35, Sep. 2014.

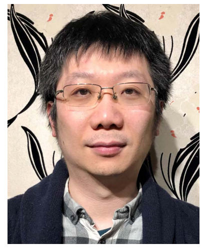
[125] A. Holland, "Risk management for combinatorial auctions," Ph.D. dissertation, Dept. Comput. Sci., Nat. Univ. Ireland, Cork, Ireland, 2005.

Nikola Bešinović received the B.Sc. and M.Sc. degrees from the University of Belgrade, Serbia, in 2009 and 2011, respectively, and the Ph.D. degree in transportation from the Delft University of Technology in 2017. He is currently a Lecturer and a Researcher with the Department of Transport and Planning, Delft University of Technology. He is also the Vice-Chair of the INFORMS Railway Application Section. His research interests include AI, optimization and analytics in public transport systems, and resilience of transport networks. He received several scientific awards, including the IEEE ITS Dissertation Award and the Young Railway Operations Researcher Award from IAROR.

Lorenzo De Donato was born in Avellino, Italy, in 1993. He received the bachelor's and master's *(cum laude)* degrees in computer engineering from the University of Naples Federico II, Italy, in 2016 and 2020, respectively, where he is currently pursuing the Ph.D. degree in information technology and electrical engineering (ITEE). His main research interests include artificial intelligence, specifically deep learning and computer vision, its applicability to the railway sector, and the study of critical railway systems.

Francesco Flammini (Senior Member, IEEE) is currently a Full Professor in computer science with Mälardalen University, Sweden. From 2003 to 2017, he has worked in private and public companies on transportation and infrastructure safety and security projects. Since 2018, he has been working as an Associate Professor with Linnaeus University, Sweden, where he has chaired the cyber-physical systems (CPS) environment. He currently works as the Technical Manager of the RAILS Research Project. He had leadership roles in more than ten research projects, has edited or authored more than ten books and 150 publications, mainly about trustworthy autonomous systems. He is an ACM Distinguished Speaker and a member of several IEEE societies, including intelligent transportation systems.

Rob M. P. Goverde (Member, IEEE) received the M.Sc. degree in mathematics from Utrecht University, The Netherlands, in 1993, the Professional Doctorate in Engineering (P.D. Eng.) degree in mathematical modelling and decision support and the Ph.D. degree in railway transportation from the Delft University of Technology in 1996 and 2005, respectively. He is currently a Professor in railway traffic management & operations and the Director of the Digital Rail Traffic Laboratory, Delft University of Technology. He also chairs the cluster railway systems of the TU Delft Transport Institute. His research interests include railway traffic planning and management, automatic train operation and train control, using operations research, optimal control, and AI. He is the Editor-in-Chief of the *Journal of Rail Transport Planning & Management*, an Associate Editor of the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, a Board Member of the International Association of Railway Operations Research (IAROR), and a fellow of the Institution of Railway Signal Engineers (IRSE).



Zhiyuan Lin received the Ph.D. degree in computing from the School of Computing, University of Leeds. He is currently a Lecturer with the Institute for Transport Studies, University of Leeds. His research interests include transport scheduling in timetables, railway rolling stock and crew, network flow optimization, speed profile multiobjective optimization for low emissions, and efficient solution approaches for integer linear programs, including both exact and hybrid heuristic methods.

Ronghui Liu received the B.Sc. degree from Peking University, China, and the Ph.D. degree from Cambridge University, U.K. She is currently a Professor in networks and transport operations with the Institute for Transport Studies, University of Leeds. Her main research interests lie in developing mathematical, simulation and optimization models to analyze the dynamic and complex interplays among policy instruments, operational controls, and traveller's behavioural responses in transportation networks.

Stefano Marrone is currently a Post-Doctoral Researcher with the University of Naples Federico II. His research topics are within the sphere of pattern recognition and computer vision, with applications ranging from biomedical image processing to remote sensing and image/video forensics. More recently, he has also been working on ethics, fairness and privacy in artificial intelligence, spending eight months with the Imperial College London (U.K.), hosted by the Computational Privacy Group, Data Science Institute. His background also covers expertise on embedded systems design, including applications for AI, approximate computing, and parallelization on multi-CPU/GPU systems.

Roberto Nardone received the master's degree in computer engineering and the Ph.D. degree in computer and automation engineering from the University of Naples Federico II, Italy, in 2009 and 2013, respectively. From 2018 to 2021, he was an Assistant Professor with the Mediterranean University of Reggio Calabria, Italy. Since 2021, he has been an Assistant Professor with the University of Naples "Parthenope," Italy. He serves as an Associate Editor for distinguished journals, such as IEEE ACCESS and *Journal of Universal Computer Science*, and has coauthored more than 60 research papers published in peer-reviewed international journals and conference proceedings.

Tianli Tang received the Ph.D. degree in transport studies from the University of Leeds in 2021. He is currently a Post-Doctoral Researcher with the School of Transportation, Southeast University. His current research focuses on dynamic management on public transport systems. He is interested in public transport planning, big data analysis, and machine learning techniques.

Valeria Vittorini is currently an Associate Professor in computer engineering with the University of Naples Federico II, where she teaches computer programming, formal methods, and risk assessment. She has coauthored more than 100 papers in the areas of verification and validation of critical systems, physical protection of critical infrastructure, formal modeling, and model-driven engineering. She is recently investigating the application of artificial intelligence to the transportation sector, and in particular to railway systems. She currently serves as the Coordinator of the H2020 Shift2Rail Project RAILS (Roadmaps for A.I. integration in the rail sector).