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8. Artificial intelligence in railway traffic planning and management Taxonomy, a systematic review of the state-of-the-art of AI, and transferability analysis

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I. INTRODUCTION

Artificial intelligence (AI) is described as a computerized system capable of performing physical activities and cognitive processes, solving a variety of issues, and making judgements without explicit human instructions (Kaplan and Haenlein, 2019). AI is becoming one of the most significant areas of study in almost all academic and industrial sectors. Unlike many other industries where AI applications have reached maturity, the railway industry is still in its infancy concerning AI. Emerging evidence has begun to demonstrate the potential of AI in railway traffic planning and management (RTPM) and suggests that AI can play significant roles such as optimizing complex railway timetables, rolling stock, and crew schedules, rescheduling trains with disturbances/disruptions, and enhancing the quality of customer service. Moreover, from a global perspective, Gibert et al. (2016) anticipate that AI will soon become a standard tool in the rail business. In recent years, the phrase artificial intelligence has been more ingrained in everyday life. Due to its extensive usage, AI is sometimes incorrectly used as a synonym for topics that are closely related, such as machine learning, deep learning, and big data.

As a result, there is often a lack of clarity on what AI represents, resulting in confusion and misunderstanding among academics and practitioners in both academic and public communications (McCarthy, 2004; Agrawal et al., 2017). Therefore, in this chapter, we first present an AI taxonomy for RTPM in Section II. Taxonomy is the classification of items based on their natural connections. It gives a shared language for discussing and exchanging information about a certain issue. Section II aims to define artificial intelligence, introduce taxonomy, and establish the required connections between AI and RTPM. It brings together these two domains by considering their respective AI and railway expertise simultaneously to define AI for the railway domain. This will open the path for a greater knowledge of AI vocabulary and ideas in the railway sector – introducing AI professionals to RTPM subdomains. In Section III, a thorough literature review of the state-of-the-art of AI in railway transport is presented. Specifically, we analysed and evaluated publications from a comprehensive RTPM viewpoint, encompassing areas such as timetabling, routing, shunting, managing railway capacity, traffic analysis and forecast, and identifying disruptions for rescheduling. Section IV further discusses the applicability of AI approaches for traffic planning and management in adjacent industries to railroads. This section then identifies and analyses the most

promising applications in the non-rail transport sectors that may be transferred to RTPM. Finally, Section V concludes this chapter.

II. AI TAXONOMY IN RAILWAY TRANSPORT

This section serves to define AI at a rudimentary level, introduce relevant taxonomy, and clarify the essential links between AI and railway traffic planning and management (RTPM). The purpose of this section is to bring together two domains, as well as experts from both AI and railways, to define AI for RTPM. This will allow railway practitioners to obtain a better understanding of AI vocabulary and concepts and introduce railway subdomains to those who have considerable expertise in AI but little knowledge about railway planning.

A. AI

AI is defined as any machine that acts intelligently (Przegalinska, 2019) or exhibits features associated with human reasoning. To put it another way, AI research strives to develop intelligent agents that think and act similarly to humans, according to this broad definition. The lack of a globally acknowledged definition of "intelligence" is the fundamental drawback of such a definition. Intelligence refers to an agent's ability of learning, understanding, reasoning, planning, and solving issues in a conceptual sense. However, quantifying, describing, and measuring these features is extremely difficult. As a result, one of the most common definitions of intelligence in the AI domain is based on an agent's ability to pass the "impersonation game", also known as the Turing test (Turing, 2009): a machine is considered intelligent if it is indistinguishable from a human during an interaction with an impartial observer.

Bešinović et al. (2021) propose an AI taxonomy with the goal of framing the complexity of AI terminology after introducing the concept of AI in the railway planning and management domain, which also considers fundamental requirements of future intelligent railways. A Unified Modelling Language (UML) class diagram (see Figure 8.1) is used to represent the taxonomy, allowing for a more formal and effective depiction. Three basic concepts comprise the proposed taxonomy:

- *AI techniques* – representing methods, algorithms, and approaches that enable systems to perform tasks commonly associated with intelligent behaviours, such as machine learning and evolutionary computing.
- *AI research fields* – representing research areas that rely on AI techniques and would not exist without them, such as expert systems, data mining, and pattern recognition.
- *AI applications* – representing cross-domain applications that leverage AI to improve performance and usability, for example, computer vision, speech recognition, planning and scheduling.

Figure 8.1 illustrates a class diagram, in which classes represent taxonomic ideas. The AI subcategories – AI technique, AI research field, and AI application – are organized based on the aforementioned definitions.

As we discussed before, artificial intelligence is commonly defined as the ability of a machine to perform tasks that would need intellect if performed by people. We broadly

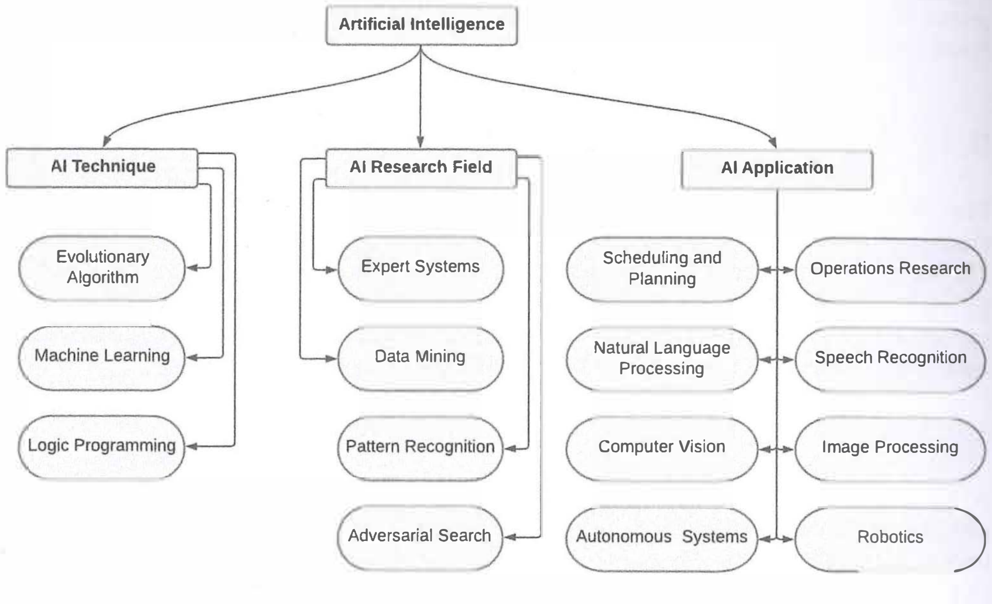

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Figure 8.1 Artificial intelligence taxonomy class diagram

investigated the methods, algorithms, and disciplines that enable an artificial entity to do such intelligent activities in practical scenarios. The following paragraphs will provide more descriptions and examples of the AI classes we defined.

The first subclass of AI technique, evolutionary computing, is formulated by biologically inspired algorithms and methodologies (e.g., evolutionary algorithms and swarm intelligence). Logic programming, as the second subcategory we identified, is a collection of programming paradigms that use first-order logic to infer new information from priors (e.g., PROLOG). And the third subcategory, machine learning, is a holistic notion that adheres to the following logic: typically, an ML algorithm can only be used within a certain learning paradigm, in a specific learning scenario, and with a fixed training modality. The learning paradigm is the strategy used to guide the algorithm during the learning process, such as supervised/unsupervised/reinforcement learning. A learning scenario describes the distinguishing features of the task under consideration, such as multi-tasking, single-tasking, and one-shot. The training modality gives information about how the training phase is implemented, for example, knowledge transfer from another task/domain (transfer learning) or training from scratch. In other words, the desired outcome would directly determine the type of ML task, such as classification, regression, or clustering. The series of operations needed to train a model, including support vector machines, tree-based, Bayesian, and artificial neural networks, is referred to as ML algorithms.

The term AI research field refers to domains/research areas that were created from the AI fundamental principles and cannot exist without it. Some notable examples in this category are represented as unsupervised machine learning paradigms. Expert systems are a branch of implementing AI into software to emulate the decision-making process of experts in

certain fields (e.g., physicians for medical imaging). Data mining (DM) is a set of procedures designed to extract information from raw data. Pattern recognition is the discipline of recognizing, detecting, and discriminating samples using data patterns. And adversarial search is the study of environments in which agents act in the presence of other opponents.

The AI application is a category linked to AI with a one-way association, which means that the former relies on the latter (and not the other way around). This class contains a lot of domains, research areas, and topics that are not strictly bound to typical AI. Nevertheless, they are increasingly relying on AI, even to the point of starting to be considered feasible only with AI. The range of AI applications is enormous. Among these, the following areas have close relevance to RTPM: scheduling and planning – a set of tools that uses AI to organize activities and processes, and operations research, in particular its subfields that use AI to improve the performance of optimization procedures, are some of the most common. The capability of a system to interpret and produce non-structured texts or sounds into understandable knowledge by machines is known as natural language processing and speech recognition. Robotics is the collection of algorithms meant to guide a robot, even giving robots human perception and behaviour. Image processing and computer vision are applications using AI algorithms to encompass image acquisition, processing, inferring, and so on.

B. Mapping AI to Railway Traffic Planning and Management

According to Bešinović et al. (2021), mapping matrices are created to demonstrate the intersections between railway traffic planning and management and AI. We define the current condition of each cell as it is recognized in scientific research and/or practice. Based on the corresponding matching, each cell receives one of the three labels: certain (Y), potential (P), or uncertain (U). Relevant publications, such as those from railways or other areas, are provided where applicable to support the conclusion of a cell. The following rules are used to identify whether an entry in the three tables belongs to Y, P, or U.

Y. Exactly matched applications can be found in academic journal/conference papers and/or successful real-world applications can be found in magazines/news or other media.
P. Similar applications of the match can be found in academic journal/conference papers and/or real-world applications. For example, an application of AI in a sector other than rail, but the principles are potentially transferable.
U. The databases cannot find any explicit literature/reports/applications, even from other related domains. In addition, we use our own discretion based on the authors' expertise and experience.

The Y cells, for example, indicate well mappings between an existing AI research subcategory and a specific task solving in railway planning and management have been found. Instead, the cells marked with P and U give the information that only a few attempts and no explicit attempts have been found, which reflects prospective research options that are worth investigating for additional in-depth studies. That is, some of those with higher matching degrees could be transferred more easily from related domains to the RTPM domain.

From Table 8.1 it can be seen that many AI research fields have been extensively introduced in railway traffic planning and management, tackling delay prediction, timetabling, and traffic rescheduling, and also including some more strategic planning decisions, using techniques

Table 8.1 *Mapping matrix for railway traffic planning and management and AI subcategories*

AI taxonomy	Subcategories	Match degree	Concerning tasks for Rail traffic planning and management	Key reference
AI research field	Expert systems	Y	Train rescheduling Train timetabling	(Schaefer and Pferdmenges, 1970) (Yin et al., 2014)
	Data mining	Y	Performance assessment Delay pattern recognition Train dispatching	(Liu et al., 2018) (Cerreto et al., 2018) (Wen et al., 2019)
	Pattern recognition	Y	Train rescheduling	(Nygren et al., 2017)
	Adversarial search	Y	Train timetabling	(Fragnelli and Sanguineti, 2014)
AI techniques	Evolutionary computing	Y	Train timetabling	(Barman et al., 2015)
	Machine learning	Y	Delay analysis Train rescheduling Train timetabling Train shunting	(Rößler et al., 2021) (Nygren et al., 2017) (Khadilkar, 2018) (Peer et al., 2018)
	Logic programming	U	-	-
AI applications	Operational research and scheduling	P	ML-based timetabling and rescheduling	(Bengio et al., 2021)
	NLP and speech recognition	P	Overall management	(Briola et al., 2013)
	Computer vision and image processing	U	-	-
	Autonomous systems and robotics	U	-	-

Source: Authors.

such as clustering, reinforcement learning, and evolutionary algorithms. The themes marked U are more adventurous, that is, difficult to realize on the technical side, or future research opportunities that appear to be underappreciated by the research community and practitioners at the time. Some of the intersections that presented U have been identified, such as traffic management and computer vision/speech recognition, autonomous driving, and logic programming, and could provide intriguing research avenues.

C. Explainable AI and AI Ethics in RTPM

Because of technological advancements, data produced in safety-critical systems, such as railways, are more difficult to be properly interpreted (Hamon et al., 2020). Explainable AI (XAI) (Arrieta et al., 2020) concerns are thus on the rise and becoming increasingly significant. Methods and strategies for making outputs comprehensible by people are referred to as XAI. XAI is concerned with three distinct concepts: interpretability (also known as transparency) is the capability of a model to be understood by a human observer, allowing interventions for making empirical decisions and improving robustness; explainability is the feature of a model to perform actions and procedures to elucidate its behaviour. The ability of a model to represent its learned knowledge in a human-understandable manner is known as comprehensibility.

RTPM is a sector where considerations of AI ethics and explainability should be addressed. Nevertheless, not all applications illustrate significant enough evidence for authorities' intervention to be justified. As a result, it is vital to concentrate attention on the specific use-case by assessing its potential hazards and consequences for human health and the environment. In general, we could say that surely the subdomain of RTPM will receive greater and immediate attention from the legislative point of view, for example, dispatching control and staff scheduling.

III. LITERATURE REVIEW AND OVERVIEW

In this section, we present a systematic literature review for recognizing the current state-of-the-art in the RTPM sector in order to comprehend the current position of AI as a whole in railway planning and management. This review bridges the gaps from defining the AI taxonomy among traditional RTPM applications towards shaping the roadmap of AI in future RTPM.

A. Graphical Overview of the Investigated Papers

In this subsection, we first analyse the selected articles by identifying the details of how the included studies are distributed over the latest 10-year period regarding their publication time. We further divide all these studies into four categories according to the tasks they oriented: rescheduling and disruptions, traffic analysis, tactical planning, and strategical planning. In addition, we classify the papers based on the specific railway topic/research focuses within each category and then two pie charts were generated accordingly.

Number of papers in each single year

We systematically inspected the selected papers by quantitatively measuring how many articles have been included in each year. We summarize the number of papers over the years in Figure 8.2.

There are only three relevant papers found that were published before 2011. The sum of available studies before the end of 2017 was noticeably lower and fluctuated between two and four. However, the number of qualified papers has significantly increased since the year 2018, exceeding eight in the years 2019 and 2020. While the number of selected papers published in 2021 and the first half of 2022 dropped to four and five, respectively.

Paper distribution in RTPM with respect to its tackled tasks

Based on the RTPM research objectives listed in Figure 8.3, the proportion of articles published in these four self-defined task categories are displayed: papers belonging to tactical planning

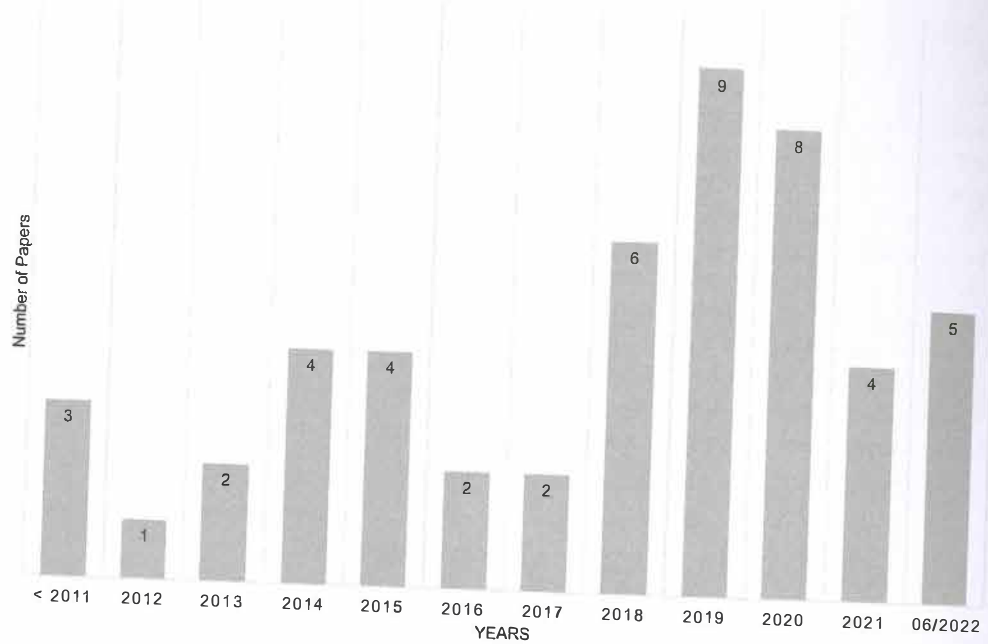

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Figure 8.2 *Distribution of papers in each year*

are the primary components, which make up 40% of the included studies – more than six times the percentage of papers in strategical planning. Up to 30% of the studies chose traffic analysis as their research objective – the second most popular task among RTPM. Researchers also have shown huge interest in disruption investigation and rescheduling tasks (with a proportion of 24%).

Paper distribution in RTPM with respect to its focused topics

AI has been greatly used to solve a variety of challenges in traffic planning and management, including timetabling, routing, shunting, managing railway capacity, traffic analysis and forecasting, identifying disruptions for rescheduling, and so on. A pie chart is depicted in Figure 8.4 to uncover the current research status on various problems/topics.

In RTPM, delay analysis/prediction yields the most prominent research attention among other problems/topics and the percentage of papers choosing this topic reached 26% – over six times the figure than those for solving conflict prediction. Rescheduling was also a popular research direction and the percentage of papers is a similar level to train timetabling problems (22% and 20%, respectively). Third, 10% of the selected papers fall into the group of railway capacity management, while the figure was slightly higher than that of track design/management, train routing, and other remaining topics.

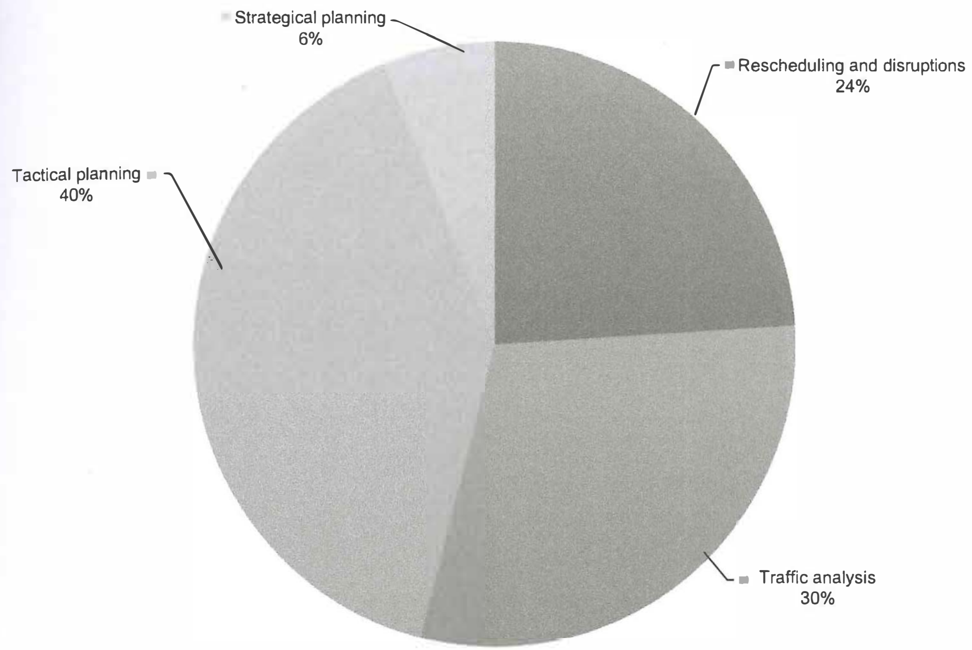

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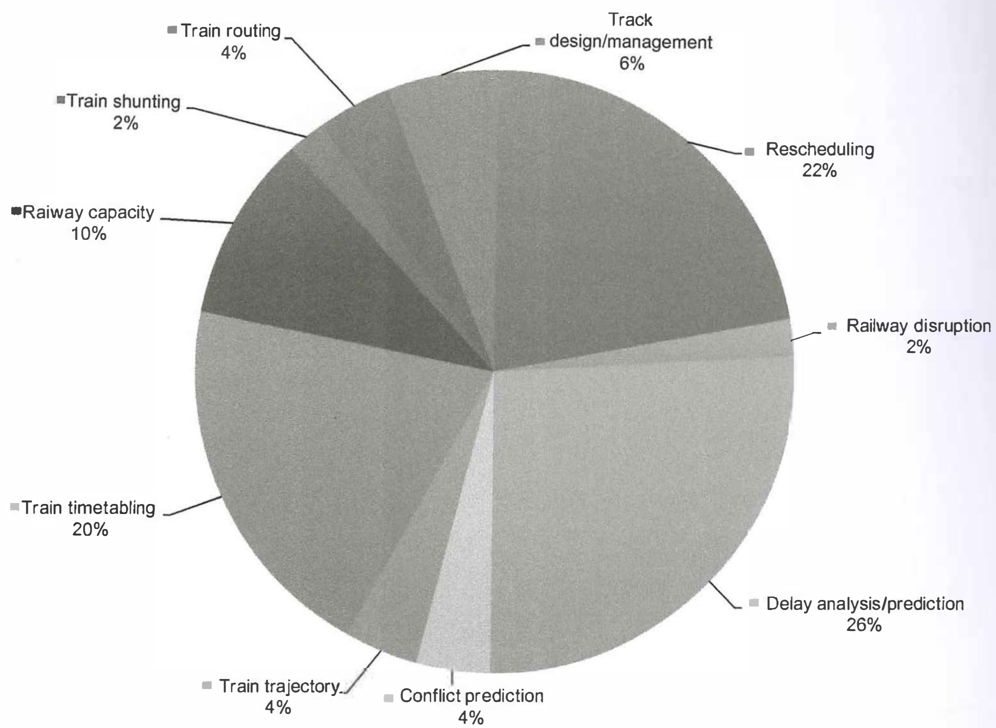
Figure 8.3 *Categorized research objectives in RTPM*

B. Paper Review Results

In this subsection, we review the included papers by clustering them based on the research objectives we defined in Figure 8.3. Within each category, we investigated the papers according to the problem they addressed and, for each paper, the exploited AI research fields/techniques/applications and utilized data are highlighted. Papers relying on (generic) heuristics or pure mathematical programming are not taken into consideration because they are not typically a branch of AI. Instead, the use of AI in mathematical programming and evolutionary programming is included in the scope.

Strategical planning

Pu et al. (2019) developed a genetic step-by-step hybrid particle swarm algorithm to optimize the process of railway routing and track alignments, particularly the three-dimensional alignment in mountainous areas. A Bayesian optimization model was compared to the genetic algorithm (GA) approach in the study by Hickish et al. (2020), which used a genetic algorithm to carry out the optimization operations of rail networks. A certain number of carriages must be distributed among trains, and line speeds were assigned in various locations throughout the network, as part of the model's test tasks. Differently, an "ontologica" system that utilizes ontologies to manage the centralized traffic control (CTC) logic of a railway track system was



Source: Authors.

Figure 8.4 *Popular research problems in RTPM*

proposed by Briola et al. (2013) for improving the experience of a user interface when using natural language queries.

Tactical planning

The tasks of scheduling, routing, and shunting have been considered in relation to tactical planning. Given that tactical planning problems are typically designing constraints for illustrating the trade-off between requests of using public infrastructure resources and limitations on these resources, and are based on which to optimize as a multi-criteria objective function. For example, a well-experienced dispatcher aims to produce a feasible timetable that ensures that there are no conflicts along the entire track line (or in a station area/depot). Diverse AI-based methods, such as bioinspired algorithms (Tormos et al., 2008; Ho et al., 2012) and reinforcement learning (RL) models (Khadilkar, 2018; Peer et al., 2018; Salsingikar and Rangaraj, 2020; Ying et al., 2020) can help to ease this procedure.

We thoroughly examined the design goals of these research studies and categorized them into two types: train operator-centred studies (e.g., Tormos et al. (2008) and Khadilkar (2018)) and quality of service-centred studies (e.g., Schüpbach et al., 2018; Xue et al., 2019; Cao et al., 2022). The first paradigm tries to provide a workable schedule that details the times of each train's departure and arrival so that the necessary resources may be allocated

to each one (e.g., rail infrastructures and facilities). Although customer-centred models focus on service quality, they also attempt to cut down on overall travel time and waiting times during transfers.

In order to reduce overall train delays, Barman et al. (2015) created a heuristic model from the perspective of the passengers, which combines a number of fixed path formulations with a GA to choose the least-time-cost path for each train. Similarly, two GA-based timetabling approaches were presented (Tormos et al., 2008; Arenas et al., 2015). Additionally, Ho et al. (2012) describe the negotiation process between infrastructure providers and train operators as a multi-objective optimization problem to create a track access rights agreement. Alternatively, Fragnelli and Sanguineti (2014) proposed a game theoretical model to optimize timetables, where train operators are able to exchange information on their own needs and are compensated by potentially increasing the resource utility. In order to solve a route optimization problem and analyse simulation results from a quantitative and qualitative perspective, Wang et al. (2019b) and Bretas et al. (2021) created a continuous multi-objective swarm intelligence system and a decentralized multi-agent system, respectively. Yin et al. (2019) developed a three-phase heuristic approach to solve a demand-responsive scheduling issue, while Goverde et al. (2016) employed a hybrid performance-based timetabling strategy where they chose a number of performance indicators to assess and create schedules.

Towards automated railway capacity planning and allocation, Noursalehi et al. (2021) performed real/short-time origin-destination (OD) demand prediction in a transit system, in which three CNN layers were used to learn spatial dependencies so that train operators could implement dynamic control strategies and provide useful customer information. To the same aim, Asad et al. (2020) leveraged historical passenger data recorded by radio frequency identification (RFID) sensors to develop a mobility and capacity prediction model. Xue et al. (2019) also used a GA to discover the best solution in a double-routing optimization model in order to utilize lost capacity at a constant departure frequency. Schüpbach et al. (2018) presented an automated schedule generation process using GA formulations in the context of the Swiss Federal Railway and provided a step-by-step methodology for a new capacity planning paradigm based on the service improvement aim.

To assign track resources to each train and optimize departure and arrival times during timetabling, a reinforcement learning algorithm was created with the aim of reducing the overall priority-weighted delay (Khadilkar, 2018). Similarly, Peer et al. (2018), Schüpbach et al. (2018), and Ying et al. (2020) used deep reinforcement learning techniques in the problems of single-track routing, metro train scheduling, and train unit shunting, respectively. In particular, to achieve superior performance to exact operational research approaches, Peer et al. (2018) and Ying et al. (2020) trained convolutional neural networks (CNNs) with the input matrices of state representations on allocations for metro trains and shunting yards.

Traffic analysis

The characteristics of statistics for large-scale railway networks include a significant number and variety of formats. The demands of finding patterns (from a huge-sized dataset) in current railway traffic may be too difficult for conventional data analysis methods to meet. Therefore, novel DM analysis tools (Wang and Zhang, 2019; Cerreto et al., 2018; Kecman and Goverde, 2014), evolutionary-based strategies (Oneto et al., 2017), graph convolutional networks (Zhang et al., 2021), and other approaches have been developed to address the challenges in delay analysis and conflict prediction. Using a supervised approach, Liu et al. (2018) built a sophisticated three-tier DM processing system for analysing train timetable performance measures (such as arrival punctuality or running time of the entire line). Cerreto et al. (2018) used a DM method based on k-means clustering to identify significant delay patterns and provide a concise explanation of the underlying causes for each clustered group of delay occurrences. Wang and Zhang (2019) proposed a gradient-boosted regression tree model to investigate how the effects of weather and timetables might affect train delays. Similar to this, Laifa et al. (2022) and Wang (2022) presented two novel two-layer light gradient boosting machine (LightGBM) models and a KNN-based classifier for predicting passenger train delays in long-distance railway and urban rail systems, respectively. Huang et al. (2020) created a model that combines a fully connected neural network with two long short-term memory (LSTM) layers in order to study operational interactions between trains, and as a result, anticipate delays. Based on this, the same group of Huang et al. (2021) designed a cost-sensitive deep learning framework called FCF-Net, which consisted of several fully connected CNN and CNNs, and these components handled train timetables as images to capture interactions of train events. Kecman and Goverde (2014) created several data-driven methodologies, including robust linear regression, tree-based algorithms (e.g., regression trees, random forest), and dynamic arc-weighted event graph models for precisely predicting running and dwell time, train event times, and expected conflicts.

In a similar manner, Oneto et al. (2017) used big data analysis techniques (such as deep/shallow extreme learning machines) to create a data-driven railway delay prediction system that took previous train movements and weather patterns into account. Additionally, Prokhorchenko et al. (2019) suggested a model to estimate the arrival time of freight trains by combining ANNs and multi-layer perceptron methods. In order to estimate arrival times for freight traffic on American railroads, Barbour et al. (2018) proposed a data-driven approach to forecast the arrival times of specific freight trains based on their characteristics, which compared the performance of various supervised ML models.

By utilizing a temporal fuzzy reasoning method, Zhuang et al. (2016) bridged the gap between a conventional methodology and an innovative solution to conflict prediction problems. Differently, Bešinović et al. (2013) proposed a program for train length prediction and offered a simulation-based method for improving the parameters in train dynamic equations of the program, which is beneficial for a more trustworthy and reliable train running time model.

Rescheduling and disruptions

Several studies have looked into rescheduling issues in disturbance and service interruption, and they have suggested solutions based on bioinspired techniques (e.g., Wang et al., 2019a) and reinforcement learning (e.g., Obara et al., 2018; Roost et al., 2020). Train-oriented and passenger-oriented goals can both be recognized as unique objectives. For example, Wang et al. (2019a) considered discrepancies between the scheduled timetable and the actual rescheduled timetable such that total/primary/knock-on train delays could be reduced accordingly, with the objective of maximizing the quality of services for passengers or increasing passenger satisfaction (e.g., Obara et al. (2018)).

To decrease the total number of trains whose delays exceed a predetermined threshold and the sum of secondary delays, Wang et al. (2019) developed a GA-based particle swarm optimization (PSO) approach. On the other hand, Kuppusamy et al. (2020) introduced a new train timetable rescheduling model that integrated the improved genetic algorithm and LSTM-RNN with the goal of minimizing power consumption by adopting the full benefits of reproductive braking energy in a random circumstance. Expert systems and knowledge-based decision support systems have recently gained attention due to their ability to drastically reduce calculation time. The suggested models, such as those by Schaefer and Pferdmenges (1970) and Fay (2000) often employ cost functions measured by the total number of delays experienced by the train. In some studies (Obara et al., 2018; Ning et al., 2019; Kubosawa et al., 2022; Zhu et al., 2020), the deep Q-network method, the deep-RL approach, and pure RL were suggested. In these approaches, an agent is in charge of adjusting running time and generating departure sequence instructions with the aim of maximizing passenger satisfaction and minimizing the average total delay for all trains along the railway line. Asynchronous advantage actor-critic RL, which was created by Google DeepMind (Babaeizadeh et al., 2016), was also employed by Roost et al. (2020). In addition, Q-learning is used in the study by Šemrov et al. (2016) to reschedule trains in a Slovenian real-world network when there are delays on a single track. The empirical findings show that this Q-learning-based method may generate rescheduling solutions that are at least comparable and frequently better than those of numerous fundamental rescheduling methods (such as first in first out – FIFO – and random walk). In contrast, Zheng et al. (2014) developed a hybrid biogeography-based optimization algorithm coupled with differential evolution to reduce the weighted delivery time in the issue of disaster relief supply operations.

Data sources

For traffic planning and management, various historical data have been used such as realized traffic movements (Oneto et al., 2017; Khadilkar, 2018), infrastructure occupation data (Kecman and Goverde, 2014; Bešinović et al., 2013; Ho et al., 2012; Schüpbach et al., 2018; Goverde et al., 2016), historical weather records (Wang and Zhang, 2019), existing train scheduled timetables (Wang et al., 2019a), the topology of rail networks (Zheng et al., 2014), and accident event data (Fink et al., 2013). For comparing the important aspects of different data types (i.e., what each type of data includes, how each type of data is collected and obtained, and the advantages/limitations challenges when they use these data), Table 8.2 summarizes the essential information.

IV. TRANSFERABILITY ANALYSIS FROM OTHER TRANSPORT SECTORS

This section addresses the transferability of AI techniques used for traffic planning and management from the aviation and automotive sectors to railways. These sectors have experienced significant progress in AI applications in the last few decades. We first present brief reviews on the application of AI in air and road transport.

A. AI-based Emerging Technologies in Aviation

Traffic prediction

The two most popular techniques in estimating aircraft arrival time are physics-based methods and machine learning (ML)-based approaches. Existing applications for the first method

Table 8.2 *A summary of the applied data sources in the literature*

Data type	Description	Typical sources and technologies used for data collection	Advantages/limitations
Traffic movements	This data measures traffic volumes, speeds, vehicle load, occupancy, travel times, etc.	Data is collected from inductive loop detectors in road pavements, automatic detection from video cameras, laser sensors, etc.	Loop detectors are not available on all road networks; they are a dated technology that suffers from lock-up and needs continuous maintenance. They only measure traffic volume and speeds. They need to be supplemented with other data to measure travel times, etc.
Infrastructure occupation data	This data includes information on infrastructure, such as the number of tracks at stations and the length of various sections, and can reflect the occupancy status of infrastructure/facility resources on stations.	Data is directly provided by the infrastructure manager/railway safety and standard board, and collected by roadside signal or block indicators. Also, occupancy dynamics can be updated by dispatchers.	Infrastructure status data is an important aspect to be considered during RTPM as most train activities are conducted based on it. However, currently the approaches to update it in a real-time manner are insufficient.
Historical weather records	Historical weather records refer to external environmental data when trains operate on the railways, including rainfall, temperature, wind speed, snowfall, humidity, etc.	Data is collected from the temperature/humidity/rainfall sensors embedded in each geometrical grid. Geographic information systems and web scraping systems are supplementary sources.	External environmental data is unstable and it always changes over time. One of the challenges is how to effectively incorporate these records into traffic modelling procedures.
Train timetables	Train timetables denote data that can be calculated based on planned and real timetables, such as arrival/departure delays, buffer times, margin, headways, etc.	Data is generated and provided by various train operating companies, which can be organized by the public infrastructure provider, e.g., Network Rail.	Train timetable data is good first-hand material to investigate how different traffic issues occur. However, it is typically difficult to acquire due to confidential agreements among different companies and stakeholders.
Topology or rai networks	Network topology structure refers to the geographical locations of all stations, the average travelling time on the edges, the connectivity status between each pair of stations, etc.	Some open sources, e.g., openrailwaymap.org. Data feeds (web APIs) provided by ORR (Office of Rail and Road).	Compared with previous data types, the network topology is more difficult to be properly interpreted and represented in a machine-friendly format.

Authors.

were often designed with a trajectory-based operation (TBO) paradigm, where the trajectory becomes one of the key features that significantly determine air traffic management capabilities. Such an implementation, called air/ground trajectory synchronization (AGTS) by Fernandes et al. (2020), aims to choose the most precise scheduled time of arrival. Ayhan et al. (2018) created a brand-new technique for predicting expected arrival times for commercial flights. To gather essential information including weather conditions, flight operations, and airport facts along the possible flight path, the system learns important characteristics from prior trajectories and its appropriate 3D grid points. Several well-known machine learning techniques, including gradient boosting classifiers (Chakrabarty, 2019; Thiagarajan et al., 2017), decision trees (Al-Tabbakh and El-Zahed, 2018), random forests (Rebollo and Balakrishnan, 2014), and hybrid models (Choi et al., 2016) have been broadly implemented in the process of aircraft delay prediction.

The majority of forecast models, such as Nilim et al. (2001), primarily concentrated on weather-related delays and how these delays spread in extreme meteorological conditions. It is now evident that an increasing number of applications predict upcoming network-related delays for a specific airline. For instance, Xu et al. (2005) were able to capture interactions/communications among airports using a systematic Bayesian network. Another established truth is that the standard machine learning-based techniques discussed above frequently perform less than optimally because the complexity and volume of data resources are constantly increasing, demanding more effective pre-processing approaches for handling the data. Thus, to this point, deep learning techniques and big data approaches are introduced, for example, by Kim et al. (2016), Khanmohammadi et al. (2016), and Belcastro et al. (2016). When tackling challenging traffic classification jobs, a hybrid structure that mixes deep learning and big data algorithms can analyse a large amount of data.

Strategic/tactical airspace planning

The global air traffic management (ATM) system now in place for civil aviation is managing a significant amount of demand, which is still increasing. This high demand can potentially lead to problems with demand-capacity balancing (DCB) issues. Given this context, an innovative AI-based solution has been presented by Amarat and Zong (2019), who are using unmanned aerial vehicles (UAVs) to execute three degrees of freedom (3D) path planning, route algorithm, and navigation. Conventional and node-based algorithms are the most popular options for path planning, according to the findings of Amarat and Zong (2019).

Air traffic flow management

The two main areas of air transport system study are air traffic flow management (ATFM) and airspace research, for example, in Wu and Caves (2002) and Tosic and Babic (1995), with the latter being particularly important to the tactical aerospace management we previously stated. Airport capacity, facility utilization, aircraft operations in the airport terminal manoeuvring area, and aircraft ground operations research are among the study subjects at the airport level (Gilbo, 1997; Bertsimas and Patterson, 1998; Ma et al., 2016; Guclu and Cetek, 2017). Future research areas of interest could include integrating airport and airspace capacity, creating airport information systems to better utilize airport capacity, and enhancing flight schedule planning to increase the accuracy of schedule implementation.

Since the early 1970s, researchers have been made aware of the difficulty in modelling and optimizing airport capacity (Zografos et al., 2017). In contrast to other public transport options, assigning flights with ground-holding delays at the origin airports is a successful strategy to prevent aircraft delays brought on by a lack of airport capacity (Terrab and Odoni, 1993). Deterministic models and stochastic and dynamic assignment models for ground-holding are some examples of solutions (Glover and Ball, 2013). An airport network's air traffic control has recently been optimized utilizing AI-based heuristic algorithms and dynamic simulation techniques (Wang et al., 2021), with the goal of analysing aircraft trajectories.

The recent increase in demand for UAVs has made managing air traffic flow even more difficult. The advancement of automated dependent surveillance-broadcast (ADS-B) technology makes it feasible to construct a more sophisticated ATFM architecture such that aerial vehicles may be followed and monitored accurately in real time. All of these developments must be built using big data technology and robust machine learning algorithms. For example, an aviation big data platform in the study of Gui et al. (2020) consists of a set of distributed ADS-B ground stations. The air traffic flow between different cities can be efficiently collected and anticipated by utilizing the extracted information collected from different datasets and mapping them along routes. The experimental findings of Gui et al. (2019) using actual data show that this new traffic flow prediction model would perform better with LSTM as the primary predictor.

B. AI-based Emerging Technologies in Road Transport

Dynamic traffic prediction

Clustering algorithms. While K-means clustering (Li et al., 2016) is regarded as an efficient and adaptable algorithm for large datasets, fuzzy C-means (FCM) (Chen et al., 2019) or original C-means methods (Yang et al., 2012) are the most often used approaches and they play a crucial part in traffic pattern detection. Except for studies using DL, because they can process input data across multiple layers, many studies utilize clustering prior to the main prediction model (Akhtar and Moridpour, 2021). To this point, clustering and data pre-processing are often carried out simultaneously, at least initially, with datasets that are primarily unstructured and unclassified.

It is difficult to generalize traffic congestion forecasting research using various methods. The study location, data collection timeframe, predicted parameters, prediction intervals, and validation process are shared elements among the pertinent publications. Several articles used the scenarios of transportation corridors and segments (Lee et al., 2015; Onieva et al., 2016; Yang, 2013). The traffic network (Yang et al., 2019; Zaki et al., 2019), the ring road (Wang et al., 2015), and the arterial road are additional study scenarios (Jain et al., 2017). The time frame of the data gathering ranged from years (Kim and Wang, 2016) to less than a day (Wang et al., 2018). Mean absolute error (MAE), symmetric mean absolute percentage error (sMAPE), and root-mean-squared error (RMSE) are the validation techniques that compare the results with the ground truth value or other models.

Probabilistic reasoning is an important part of the conventional definition of AI from a semantic perspective. For coping with ambiguous knowledge and reasoning, it has been used extensively in the comprehension and identification of traffic congestion. Traffic data are growing more complicated and non-linear due to the length of the timeline and spatial dependence. Fuzzy logic is now a widely used technique for predicting dynamic traffic congestion due to its superior capacity to handle ambiguity and vagueness in place of binary results (Onieva et al., 2012). The most popular fuzzy logic implementation in studies on traffic engineering is the fuzzy rule-based system (FRBS). By simulating them in operational IF-THEN rules, it is able to handle the complexity that results from real-world traffic conditions. In practice, these rules are optimized by using different GAs. For example, Daissaoui et al. (2015) integrated the Ant colony optimization (ACO) algorithm into the fuzzy logic system to predict traffic congestion one minute in advance from the moment that information is provided by passing cars. The GPS information from each vehicle was interpreted as a pheromone, which is congruent with the idea of ACO.

Tactical road capacity planning

IoT-based approaches can be easily introduced into smart objects to simulate human learning processes, although cognitive computing has recently grown in favour of IoT, frequently alluded to as the cognitive IoT (CIoT). In the past, drivers assumed entire responsibility for controlling the vehicle in a variety of unforeseen circumstances, such as lane changes and lane acceleration. However, human drivers may be inattentive or distracted, which could result in irrational outcomes like a collision, choosing the wrong route, and speeding. The intelligent transportation system is able to carry passengers in the most secure and effective manner from the viewpoint of public transport. Accessing real-time data right after they are produced is necessarily important for reaching this degree of efficiency. Transport will be safer as a result of the increased accuracy of traffic flow brought about by the connectivity possibilities between vehicles and traffic control centres. A dynamic map of traveller flows will be generated accordingly, for instance, by analysing the trajectory/volume data that is acquired by sensors, cameras, and IoT equipment that is dispersed on buses, trains, and subway systems. Because of this, intelligent route planners can analyse each person's movements individually and make recommendations that are more precise than experts.

For people who want to take the bus, Puiu et al. (2017) have created an app that offers route suggestions and alerts about incidents. Real-time bus arrival-departure data streams and citizen-reported incidents were processed to complete this application. Each user in this system contributes to the network's real-time traffic and IoT information feed while also receiving benefits from it.

MLP-based methods. The scope of conventional road traffic planning and management was undoubtedly expanded by successful trials of finding potential travel routes. For instance, Hu et al. (2020) used the open data resources of Google Maps and its "multiple destination" function to search for potential routes between origin and destination in order to meet the demand for a delivery service at the end of this commercial chain, which was a brave attempt to face the demand of ever-expanding e-commerce businesses. For the purpose of simulating traffic conditions, these routes were fed into a multi-layer perceptron model. Dijkstra's algorithm would generate the best route selection. After calculating every route that could possibly exist between the starting point and the final destination, the ANN components help to forecast how congested each of those paths will be. Notably, the information from the transportation records, such as the average speed, travel distance, and idle driving time for each vehicle, as well as the weather conditions for each trip, significantly increase the forecast accuracy. Experimental results of Hu et al. (2020) show that the multi-layer perceptron (MLP) model reached a stable prediction accuracy when it was trained with more than 170 epochs, with an accuracy of 95% or more.

Traffic flow management

Parametric methods. Time series models (Ishak and Al-Deek, 2002) and Kalman Filtering (KF) (Lippi et al., 2013) are two frequently used techniques in parametric methods. Except when there is noise and disturbance in the network, parametric approaches have a higher accuracy with fewer errors during prediction than non-parametric approaches. Even in a given environment, traffic flow prediction can differ significantly since it is determined by a number of variables, including the forecasting horizon, dataset format, type of area, and sampling frequency. Due to the ambiguity and complexity of traffic flows, studies focus largely on short-term prediction methodologies rather than extending their horizon into days (Akhtar and Moridpour, 2021). The accuracy of the anticipated output typically decreases as the forecasting horizon value increases and vice versa.

Non-parametric methods are preferred by researchers due to their capabilities of dealing with stochastic, non-deterministic, and non-linear characteristics of traffic data. Deep learning-based techniques are frequently employed in predicting local and worldwide traffic flow because of their well-known capability in handling a large amount of complicated spatiotemporal data (Smith and Demetsky, 1997). We identified three techniques among other candidates that have been used the most for road traffic flow estimation: LSTM, CNNs, and recurrent neural networks (RNNs), or a combination of them (Nguyen et al., 2018). In addition to these, applying deep belief networks (DBNs), autoencoder-autodecoder (AE-AD), and deep Boltzmann machines (DBMs) to traffic flow prediction were described or investigated.

With the use of computer vision techniques, automatic video analysis from traffic surveillance cameras has recently become a promising field. It has already been established as one of the rapidly expanding fundamental technologies for efficient traffic management and intelligent transportation systems (ITS). In parallel traffic management systems (PtMS), one of the crucial techniques for gathering traffic state information is video detection (Vishwakarma and Khare, 2008). To put it another way, although tracking and recognition of moving objects in surveillance video is not a difficult task given their non-deterministic nature, it is important because it provides the groundwork for more advanced intelligence applications.

Vehicle detection and categorization technologies have important theoretical implications and practical utility in intelligent transportation systems. A novel vehicle classification framework that can automatically interpret photos from traffic surveillance systems was proposed by Hannan et al. (2015). The convolutional neural network serves as the second-layer classifier in this system, with the fast neural network (FNN) serving as the primary classifier. The multi-layer perceptron used by the FNN to create potential correlations between the input and the weighted neurons allows for highly accurate detection. A lighting normalization algorithm is used in the CNN layer to lessen the impact of fluctuations in illumination. In contrast, Khalid et al. (2011) offered a new approach to vehicle detection where the processed images were captured by embedded cameras that were mounted on each moving vehicle. A sophisticated model recognition technique that can accurately identify the car type and manufacturer was developed by Psyllos et al. (2011) based on their research. Multi-colour recognition was added to this method to produce an output that was more dependable.

A significant component of traffic pattern recognition is the analysis of public traffic surveillance, such as highway surveillance footage, in addition to the vehicle appearance photos gathered from various sources. Automatic driving and cruise control would substantially benefit from these techniques, which are important for detecting vehicles ahead of you and recognizing traffic conditions. To realize automatic segmentation and recognition of the road regions, for instance, Kong et al. (2013) provided a method for automatically recognizing the frequency domain features that are produced by the vehicles moving through road areas in movies.

C. Potential Directions for Transferability

In this part, the most promising applications that can be transferred from the origin domains (those we identified in subsections IV.A and IV.B) to the target domain (i.e., RTPM) are presented. The discussion about how/to what extent AI-based solutions have been adopted in aviation/automotive transport sectors in typical RTPM tasks will be illustrated. As a significant outcome of this section, several potential directions for transferability are identified.

Integrating heuristic searching strategies with deep neural networks for vehicle routing

In terms of the tasks of path planning, route algorithm, and navigation for aircraft, graph-based methods, especially the critical link method and queuing theory, are more popular in unmanned aerial vehicle path planning compared with the traditional node-based methods. Adding values to the railway sectors based on this observation can be summarized as follows: unlike aircraft, railway vehicles must run on constructed tracks and follow the instructions of dispatchers to move/halt. Path planning on public transportation systems from the macro scope level, although conceptually similar, is a significantly harder problem, not only due to its inherent time-dependent and multi-criteria nature but also considering that most railway networks have the characteristics of heterogeneity. Thanks to the hints obtained from the aviation sector, a method based on the generalized cost can be proposed to discover the valid routes from the original station to the destination station for trains in the integrated network of normal-speed and high-speed railways, especially in the circumstances that the high-speed railway network is expanding rapidly among areas of Europe and China. The potential influential factors include total travelling time, total energy consumption, number of onboard passengers, the capacity of chosen tracks, and other possible factors in the generalized costs of trains. Theoretically, valid routes can be generated by considering the defined train schedule, and an effective route-search algorithm can be designed using the deep traversal method in a new valid route-searching network.

As we already discussed, formulating a simple heuristic is challenging under the road network setting since there are multiple factors to consider, such as road segment length, edge centrality, and speed limit. Recently, a novel study investigated how a neural network can learn to take these factors as inputs and yield a path given the origin and destination in the road network, which may give us some inspiration about how the DNN can contribute to railway path planning tasks. First, some random graphs can be generated by monitoring the size and properties of the training graph without too many details about the network. Then, a neural network can learn to traverse simple graphs with multiple strategies. Finally, factors that might affect path finding in real road networks are scaled up. Overall, the training data are optimal paths in a graph generated by the shortest path algorithm. The model is then applied to new graphs to generate a path given the origin and destination. The arrival rate and time efficiency are calculated and compared with that of the corresponding optimal path. Such a method investigates and innovatively combines deep traversal strategies and deep neural networks to perform route planning for vehicles.

Alternative routes services/navigation for passengers based on CIoT

In this application, transferability possibility from the perspective of the passenger (microscope) is described – compared to train vehicle routing, travel route selection for individual passengers is also important. Passengers on the same train typically have different destinations – there are a set of intermediate stations between the original and terminal stations and each passenger may leave the train at any of the intermediate stations as they need, even transferring to another train. The behaviour/travelling patterns of the individual passenger are more difficult to capture and simulate when using mathematical methods or heuristic search algorithms. The considered quantitative parameters include total travelling fare, travel time, transfer difficulties, travel convenience, comfort, and other possible factors in the generalized expenses of passengers. Relevant studies regarding this consideration have been found but they are limited. Most of them investigated travel time reliability and the estimation of passenger route choice behaviour. By leveraging the inferred platform elapsed time and the transfer time from the smart card transaction data, the journey time distribution of any possible path can be generated, and methods were proposed for estimating route choice proportions.

Current research on IoT focuses on the general perception of visual/voice objects and making this information connected to sharing observations and making decisions. However, it is not enough that only connections are established, the agent should have the capability to learn from external inputs, think independently, and understand both physical and social environments by themselves. Therefore, a new paradigm, CIoT, has received attention in empowering current IoT with an "intelligent brain" for higher-level automation. Typically, an operational CIoT framework mainly characterizes the interactions among five fundamental cognitive tasks: the perception-action cycle, massive data analytics, semantic derivation and knowledge discovery, intelligent decision-making, and on-demand service provisioning. Compared with traditional passenger route design services, the CIoT framework has the capability to bridge the physical world (with physical objects, facility resources, etc.) and the social world (with human demands of travelling, social behaviour, etc.), and enhance tasks of smart resource allocation, automatic network operation, and intelligent service provisioning. From the literature we have found several promising studies related to this topic, some of them specifically improve the performance of services for railway users (e.g., the rail Internet of Things (RIoT)), but others may enlarge their scope under public transport systems (e.g., the cognitive road traffic management system (CTMS)). Solutions found in the automotive sector show a medium level of advancement and promise for the rail sector.

Attributing primary and secondary delays in railway networks using explainable AI

Motivations of proposing this application include two aspects: the first one is the research direction of explainable AI (XAI) needs to be synchronized with the investigated railway research areas for narrowing the research gaps that could hinder operational deployment. Second, understanding/labelling/learning knowledge from massive data is difficult and it has not been fully understood at this stage, so we need a powerful framework to explain the mechanism of AI models to those who are experts at traffic planning and modelling but have little working experience on the AI side. Explainable AI is becoming more important as many AI systems are too complex to be properly understood by humans; therefore, XAI approaches and methods are necessary to make the reasoning process and the outputs understandable by human operators.

On the one hand, the problem of discerning different reasons why train delays occur is tough and complex. Train dispatchers want to know which train builds up a delay at which station, as well as why this delay build-up occurs. On the other, XAI has not received extensive practical attention in the rail sector, and where the authors have tackled the problem of discerning different reasons for the occurrence of train delays. Hence, there is much interest in the causes of delays, as different causes imply different ways to prevent these delays from occurring. Given the total amount of delay a specific train builds up at a specific station, we discern the primary delays that would have occurred if there had been no other train in the network, such as vehicle problems, from secondary delays that are knock-on delays. The proposed approach is to train an ML model that predicts the additional delay of a train, given a set of primary features (e.g., weather conditions) and secondary features (e.g., the delays of nearby other trains). Methods from explainable AI help to classify how primary features and secondary features contribute to a specific prediction of the model.

V. DISCUSSION

This chapter has provided a comprehensive review of scientific papers addressing the state-of-the-art AI in the railway sector. We reviewed papers from a holistic railway perspective, covering subdomains such as strategical planning, tactical planning, traffic analysis, and rescheduling after disruptions. As such, this chapter presents a first step towards the adoption of AI in the RTPM domain by providing an in-depth summary of the current research focus. In addition, we identify some promising research directions to provide further uptake of AI in railways.

In the domain of RTPM, although pure mathematical/exact operation research algorithms are popular for those who want to find the upper limits of optimization performance, effective AI approaches (e.g., data mining, reinforcement learning, and expert/knowledge-based reasoning system) have been gradually adopted thanks to their advantages over exact methods, especially when the problem is NP-hard and it is difficult to yield an optimal solution within limited computational time. However, optimization-based solutions to support traffic analysis and tactical planning have their own advantages over heuristic approaches (i.e., genetic algorithm, evolutionary computing and particle swarm optimization) in solution quality and robustness.

Conventional machine learning models (i.e., regression trees, decision trees, random forest, support vector machine) have been widely adopted in solving rescheduling, timetable design, and train routing problems. Furthermore, they are effective ways within big data analytics to identify delay patterns and estimate the delay level for both passenger railway lines and the freight network. The techniques listed above, together with pattern recognition, have been applied to address various problems according to their objectives and acquired data. For example, systematic data processing and cleaning frameworks, such as feature engineering, clustering, or encoding of time-series data are likely to be adopted against a background of hybrid large-scale data resources. On the other hand, a rescheduling problem is about finding a feasible new timetable after disruptions and thus may require previous experiences in dispatching, giving the potential of applying supervised machine learning methods.

All in all, different approaches demonstrate their potential in different application scenarios. It is difficult to outline which approach is the most promising one over others. In other words, it largely depends on the requirements of data pre-processing and the purpose of the study. However, the applications of machine learning and reinforcement learning are still at their early stage and may require further development for satisfying more complex industrial/business needs. Limited work has been done in the directions of natural language processing, computer vision, and image processing, thus, the possibility of incorporating these AI applications into future research paradigms should be investigated.

VI. CONCLUSIONS

In this chapter, a taxonomy for AI in RTPM is defined. It provides a thorough description of AI for railway scholars, practitioners, dispatchers, and decision-makers. We divide AI into three categories: research fields, key techniques, and applications, and describe their main characteristics in order to confront the complex world of AI and bring it to trains.

A systematic literature review was conducted on research papers applying AI to RTPM mainly between the years of 2011 and 2022. Several mainstream AI techniques were identified. Most RTPM problems are formulated as NP-hard discrete optimization problems. While exact methods are able to find mathematically optimal solutions, they are often limited by problem size (Alfieri et al., 2006; Lin and Kwan, 2016). Traditional evolutionary-based heuristics such as GA, ant colony, and particle swarm are thus applied as a compromise (Li et al., 2021; Wang et al., 2019a). The disadvantages of these evolutionary methods are that they usually cannot guarantee the quality of solutions and are less robust and transferable. Machine learning-based optimization methods may give a promising direction in the future, which may serve as a trade-off between exact and evolutionary approaches (Bengio et al., 2021). ML models such as regression trees and RL are also commonly used for optimization problems in RTMP, for example, Obara et al. (2018), Khadilkar (2018), and Salsingikar and Rangaraj (2020). ML models are also useful in big data analytics for estimating delay levels and identifying delay trends for both passenger and freight trains (Wang and Zhang, 2019; Prokhorchenko et al., 2019; Barbour et al., 2018). In accordance with the objective challenges, different strategies, along with pattern recognition and data mining techniques, were implemented in various contexts. A framework of hybrid large-scale data is required to perform systematic data processing and cleaning, such as feature engineering, clustering, or time-series data encoding. This requirement has been observed particularly in the areas of delay analysis and conflict prediction (Liu et al., 2018).

Finally, an overview of emerging AI-based technologies in air and road is given, followed by a transferability analysis to identify which of the existing research/solutions in the aviation and automobile sectors may be applied to RTPM, for example, integrating heuristic searching strategies with deep neural networks for rail vehicle routing, alternative route services/navigation for passengers based on CIoT, and attributing primary and secondary delays in railway networks using XAI.

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