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A review of artificial intelligence in train driving and control

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Abstract

Purpose – In recent years, the rapid advancement of artificial intelligence (AI) has exerted profound impacts on and provided strong impetus to numerous fields in the industrial sector. Within the railway industry, AI has driven continuous upgrading and optimization of intelligent train control technology, thanks to its enhanced computational capabilities derived from advanced algorithms and models, as well as its role in improving safety performance. Integrating AI technology more extensively into train autonomous driving and control has thus become an inevitable trend in the global development of railways.
Design/methodology/approach – This paper, therefore, conducts a comprehensive analysis of the development progress and current status of AI technology applications in the field of train driving and control on a global scale. It systematically sorts out and analyzes the advantages of various AI technologies and the positive impacts they bring to the upgrading of train control technology, elucidates the feasibility and future prospects of applying a range of emerging AI technologies from the perspective of technical theory and provides guidance for the intelligent development of this field from a practical perspective.
Findings – The application of AI technology in the train driving and control field is still in its infancy. While a large number of AI technologies have been widely adopted, there remains significant room for further optimization and improvement of these technologies. Additionally, a variety of AI technologies that have been applied in other industrial sectors but not yet widely implemented in training autonomous driving and control have demonstrated tremendous development potential.
Originality/value – The research findings provide references and guidance for advancing train control technology, promoting the digital transformation of railways, accelerating the overall optimization and upgrading of railway industry technologies, and facilitating the accelerated development of global railways.

Keywords Autonomous train driving, Artificial intelligence, Train control, Train safety, Quantum computing
Paper type General review

1. Introduction

Artificial intelligence (AI), a research domain within computer science, empowers machines to learn from data in a manner analogous to human cognition, leveraging the insights derived from learning to achieve predefined objectives and solve complex problems that are intractable with conventional computational approaches. Today, with continuous technological advancements and breakthroughs, AI has emerged as a cornerstone research field in almost all industrial sectors. However, its application in the railway industry still remains in an embryonic stage. Numerous scholarly works and empirical studies have underscored the transformative potential of AI in rail transport, demonstrating its efficacy in diverse areas such as signal control, scheduling optimization, autonomous driving and fault diagnosis. However, substantial research gaps, opportunities for enhancement and technical challenges persist. For instance, existing research indicates that although a large body of literature explores the application of AI in railway maintenance and inspection, studies on

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transport policy formulation and revenue management are still notably limited (Tang *et al.*, 2022). A 2020 review of AI applications in high-speed rail, particularly in the domains of intelligent planning, control and maintenance, highlighted the formidable challenges posed by ensuring system safety and stability, underscoring the need for further inquiry into these critical dimensions (Yin, Li, & Cheng, 2020).

Over recent years, practitioners have witnessed the extensive application and rapid evolution of AI technologies in high-speed rail systems, with novel advancements, applications and technical upgrades emerging almost annually. A recent study has indicated that, driven by emerging services, high-speed rail systems require continuous breakthroughs in autonomous driving and digital services, thereby accelerating the integration and application of AI technologies, with sub-directions such as train energy consumption optimization, communication and safety, and intelligent high-speed rail platforms becoming current and future research hotspots (Li *et al.*, 2024b). Most of these technologies or subdomains are closely related to train driving and control, demonstrating the extensive applications of AI in the field of train control. Practitioners have studied and validated the application of AI in training autonomous driving, confirming that AI-based speed control methods outperform traditional approaches, and this outcome underscores the advantages, practicality and significance of AI technologies (Plissonneau, Trentesaux, Ben-Messaoud, & Bekrar, 2021). However, research on applying AI technologies to the critical direction of train driving and control remains insufficient. With the breakthroughs and upgrades in AI technologies, substantial research gaps exist in the application of AI in this domain, and this study thus focuses on this specific domain.

To understand the overall application status of AI in the field of train driving and control and analyze future research directions, this paper reviews various cutting-edge studies and technologies within this domain. The objective is to clarify the current research achievements of global researchers and scholars, as well as the status of technological applications, and to provide critical insights and perspectives for practitioners, thereby offering practical recommendations for future development and research directions in the field. More importantly, the work presented in this paper is expected to contribute substantially to bridging the existing research gap in the application of AI technologies to the autonomous driving and control of trains. It is anticipated that this paper will be valuable to the following groups: entry-level practitioners who have just entered the railway field and focus on intelligent train control; researchers from other railway technologies or fields who wish to acquire knowledge related to train autonomous driving and control for a broader understanding of industry development; scholars familiar with relevant technologies and engaged in a specific technology within the research scope of this paper, aiming to gain a comprehensive understanding of global research progress; and senior practitioners in the field who seek to focus on future prospects and key directions, broaden their thinking and prepare for subsequent research.

The remaining sections of this paper are organized as follows. Section 2 provides a summary overview of three crucial subsystems of the train automatic supervision system, summarizing their significance, functions and technical principles. Section 3 selects and analyzes six aspects where AI technology has been widely applied in train driving and control, along with cutting-edge research, primarily focusing on the existing studies in these six directions and conducting a moderate discussion on their significance or prospects. Section 4 prospectively proposes and analyzes nine technologies or future research directions relevant to the research content of this paper. Finally, Section 5 presents conclusive remarks.

2. A brief introduction to the automatic train control system

The Automatic Train Control (ATC) system is the core integrated system for achieving automated train operation control in the railway transportation domain. Through the integration of multiple subsystems working in coordination, it realizes safety monitoring, scheduling management and autonomous driving of trains, serving as a key technical support for modern rail transit, including urban rail transit, high-speed railways and intercity railways (Yin *et al.*, 2017). The core objectives of the ATC system are to enhance transportation efficiency, punctuality rate and passenger experience while ensuring the safe operation of trains, and simultaneously reduce manual operation costs and the risks of human errors. The ATC system is typically composed of three major subsystems: Automatic Train Supervision (ATS), Automatic Train Protection (ATP) and Automatic Train Operation (ATO), forming a "trinity" control architecture. Through precise control of moving block technology, deep integration of AI technologies and continuous innovation in safety architecture, the ATC system is driving rail transit toward unmanned, low-carbon and collaborative development (Pencheva, Trifonov, & Atanasov, 2022). Currently, with the continuous advancement of diverse AI technologies, numerous high-efficiency novel solutions have emerged for addressing train control-related issues. Researchers proposed a framework utilizing generative AI to optimize virtual train marshalling systems in 2025, thereby enhancing train safety (Zhu, Ye, Wang, Yu, & Tao, 2025). From perspectives of efficiency, accuracy and safety, such innovative control algorithm frameworks exert substantial impacts on train operation and control, which also underscores the immense potential of AI technologies.

2.1 Automatic Train Supervision

The ATS system, as a top-level management module of the ATC system and a core subsystem of railway signaling systems, is responsible for formulating, real-time monitoring and dynamic adjustment of train operation plans across the entire line (Dimitrova & Tomov, 2023). The ATS system is regarded as a socio-technical system because it is a purposeful system composed of humans and multiple types of equipment interacting to perform specific tasks, inherently susceptible to influences from the environment (technical, social, economic, political, etc.) while simultaneously exerting counter effects on it (Wang, Fang, Guo, & Niu, 2019). Its core functions include real-time train tracking, timetable management, route control and fault warning. Through the Man–Machine Interface (MMI), it provides dispatchers with visualizations of train operations, such as real-time position, speed and delay status, to facilitate train operation control interaction (Yu, Dou, & Sun, 2020). Train operation control interaction is illustrated in Figure 1. When the dispatcher manually controls the train through the MMI, the Train Regulation Service receives the command and transmits the control

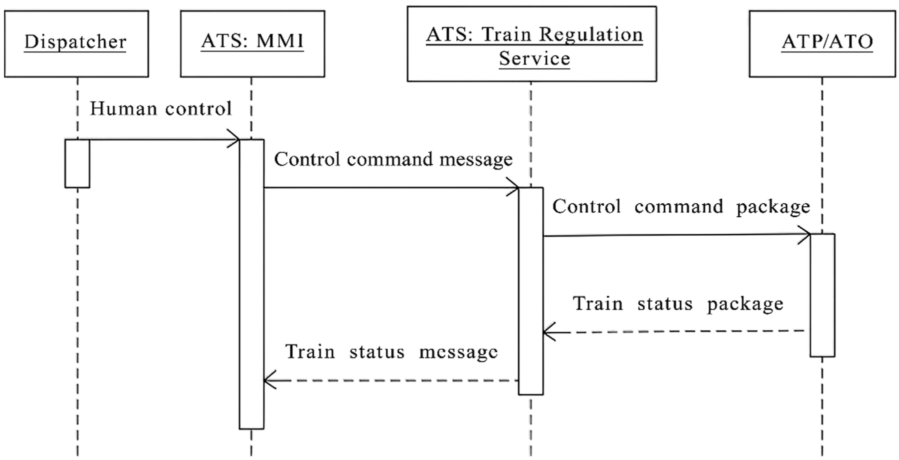

Figure 1. Train operation control interactive modeling. **Source(s):** Yu *et al.* (2020)

message to the ATP/ATO system. Upon completing the execution of operation commands, the ATP/ATO system feeds back the results to the ATS system.

Safety is a central consideration in the design and operation of the ATS system, which must strictly adhere to functional safety standards (e.g. IEC 61508, EN 50128). The system implements full lifecycle management of safety risks through anomaly detection, logging and classification mechanisms, ensuring that potential hazards are identified, analyzed and mitigated systematically (Li *et al.*, 2017). By integrating real-time monitoring, log analysis and proactive maintenance, the ATS system establishes a closed-loop safety management framework that spans from risk identification to responsive disposal, thereby enhancing the overall safety integrity and operational reliability of the rail transit system. Wang, Fang, and Bao (2025) investigated dispatchers' trust levels and degrees of reliance on safety warnings from the ATS system, and how trust levels influence dispatcher behavior. The study provides valuable insights into enhancing trust in automation for safety-critical systems, such as designing user-friendly MMI interfaces and developing targeted training programs. Zhu *et al.* (2023) proposed a proactive reliability-aware fault recovery method for the ATS system deployed on urban rail transit cloud platforms, which helps improve on-time performance and safety. It can be anticipated that with the increase in technical complexity, policy compliance pressures, industry digital transformation and the rise of interdisciplinary research paradigms, safety issues, as a core theme of ATS system research, will become a research hotspot in academia in the near future.

2.2 Automatic Train Protection

ATP, the core safety subsystem of the ATC system, ensures safe train separation and overspeed protection by continuously monitoring train speed, position and operational environment. The ATP system employs a vehicle-ground collaborative architecture comprising on-board equipment and wayside infrastructure (as shown in Figure 2). Wayside components transmit critical information to trains via track circuits, balises or wireless communication (e.g. LTE-M), including track parameters, temporary speed restrictions and the location of preceding trains. Upon receiving this data, the on-board ATP integrates real-time train-specific parameters (such as braking rate and wheel diameter compensation) to compute dynamic protection curves, which are continuously compared with actual speed profiles. When detecting overspeed or potential collision risks, the onboard ATP enforces a three-level braking strategy, such as audible alarms, service braking and emergency braking, to decelerate the train safely.

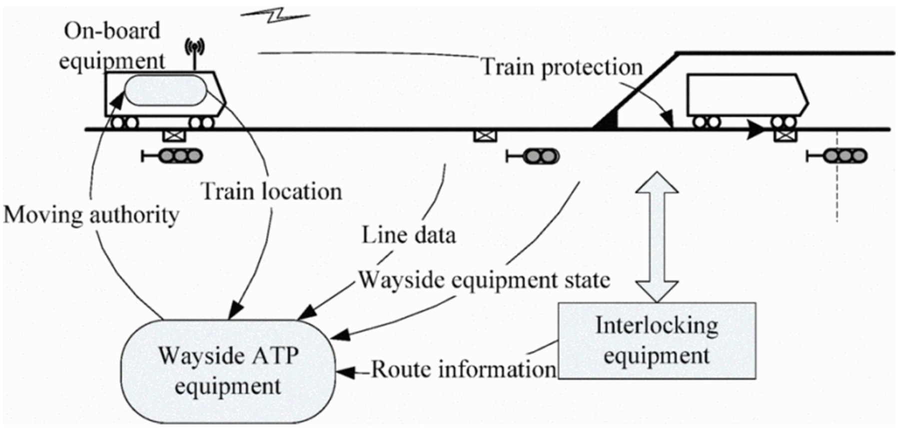

Figure 2. Structure and principle of ATP system. **Source(s):** Wang, Gao, and Liu (2009)

In international railway industry standards, ATP systems are typically required to achieve Safety Integrity Level 4 (SIL 4), the highest safety integrity level as defined in EN 50128. Meanwhile, the verification of ATP system safety has been a prominent research hotspot in academia, with studies including those by Xiong, Liu, Zhang, and Ding (2010) and Wang, Liu, and Gao (2009).

In high-speed railways, the ATP system is critical to ensuring train safety and efficiency. It employs a redundant architecture to interface with external systems such as the train control and monitoring systems, comprising key components including the Vital Computer (VC), Speed and Distance Processing Unit (SDU), Balise Transmission Module (BTM), Track Circuit Reader (TCR), Driver Machine Interface (DMI), Train Interface Unit (TIU), Global System for Mobile Communications-Railway (GSM-R) and Journey Recorder Unit (JRU) (Kang *et al.*, 2021). These sub-components collaboratively operate to maintain operational integrity, such that any equipment failure can consequently impact train performance and safety. A study has proposed a method based on Long Short-Term Memory (LSTM) neural networks for online anomaly detection and fault prediction in the ATP system of high-speed trains (Kang *et al.*, 2022). This approach presents new insights for the development of ATP systems and intelligent operation-maintenance platforms, as well as for enhancing safety. With the continuous evolution of LTE-M technology and the progressive deployment of 5G-R communication systems, the ATP system is expected to undergo continuous upgrades and advancements.

2.3 Automatic Train Operation

The ATO system serves as the “execution terminal” of the ATC system. Under the safety protection of the ATP system, it accomplishes functions including automatic operation between stations and precise stopping by accurately controlling train traction, braking and door operations. The ATO system is designed to autonomously drive trains, enabling end-to-end automated control over the entire process from departure, acceleration, cruise, deceleration, to precision stopping (Dimitrova & Tomov, 2021). Meanwhile, it optimizes energy consumption and passenger comfort. A typical ATO system comprises a three-level architecture of Perception Layer–Decision Layer–Execution Layer, which collaboratively operate. The Perception Layer achieves real-time acquisition of line parameters (gradient and curvature), train status (position and speed) and environmental data (weather and track condition) through vehicle-mounted sensors (e.g. speedometers and accelerometers) and wayside equipment (e.g. balises and track circuits) (Nicodeme, 2022). The Decision Layer generates optimal driving curves based on Model Predictive Control (MPC) and Reinforcement Learning (RL) (Liu *et al.*, 2018). The Execution Layer achieves precise train control by transmitting traction/braking commands from the on-board controller to the vehicle’s traction/brake systems via the TIU and vehicle bus (e.g. Multifunction Vehicle Bus, MVB).

The International Electrotechnical Commission (IEC) defines five automation levels ranging from GoA0 to GoA4 (Automation Level 0 to Automation Level 4) (Standard IEC 62290-1, 2025), which are specified as follows:

GoA0: Visual Operation. The train driver assumes full responsibility for driving and relies on visual observation to operate the train, and the system does not need to supervise their operations; however, the system may conduct partial monitoring of switches and monorail sections.

GoA1: Non-Automated Operation. The train driver is located in the front cab of the train, responsible for observing the track and stopping the train in case of hazards; acceleration and deceleration are executed by the driver based on information displayed in the cab or wayside signal instructions. The system continuously monitors the train’s operation, and the safe departure of the train (including door closure) is the responsibility of operating staff.

GoA2: Semi-Automated Operation. The difference from GoA1 lies in that the train's acceleration and deceleration are controlled automatically by the system, and the system continuously monitors the train's speed; the safe departure of the train is the responsibility of operating staff (door opening and closing may be completed automatically by the system).

GoA3: Unmanned Operation. Compared with GoA2, this automation level requires additional measures, as there is no driver in the front cab of the train to observe the track or stop the train in case of hazards. At this level, the train must be equipped with one operating staff member, and the safe departure of the train (including door closure) may either be the responsibility of the operating staff or completed automatically by the system.

GoA4: Unattended Operation. Compared with GoA3, this automation level requires additional measures, as there is no operating staff on board the train. The safe departure of the train (including door closure) is completed automatically by the system, and the system must support the detection and management of hazardous situations and emergency events (e.g. passenger evacuation); manual intervention may be required for some major emergency events (e.g. derailment) (Standard IEC 62290-1, 2025).

Currently, both GoA3 and GoA4 are applied in mainline railways worldwide. An important distinction between GoA3 and GoA4 lies in the switching of driving modes: in GoA3, the transition of train operation grades from higher to lower levels and driving mode changes are implemented after driver confirmation, whereas GoA4 full-automatic operation systems achieve driving mode switching (Driving Mode Switch, DMS) automatically.

3. AI techniques for autonomous train driving and control

In this section, we provide a focused review of the core technical domains in autonomous train driving and control where AI has achieved substantial applications. Currently, AI has found extensive applications in the domain of autonomous train driving and control, with most AI-driven technologies relying heavily on data sources and Verification and Validation (V&V). Data sourcing and preprocessing serve as the foundational pillars for AI model development, constituting the data enablement module within the methodological support layer. Their core function is to furnish high-quality, reliable datasets for subsequent algorithm training, simulation validation and system deployment, ensuring that AI models can accurately capture the dynamic characteristics of railway scenarios (Wang, Trivella, Goverde, & Corman, 2020). As the pivotal checkpoint for transitioning AI systems from lab-scale prototypes to operational deployments, V&V belongs to the reliability assurance module of the methodological support layer. Its primary objective is to ensure that AI algorithms meet the rigorous requirements of the railway industry in terms of functional safety, robustness and compliance (e.g. the safety integrity level classification for railway control software specified in EN 50128) (Nowakowski, Bojarczak, & Łukasik, 2018). Within the realm of autonomous train driving and control, data sources constitute the sensory foundation of the system, while V&V acts as its safety barrier. This synergy is twofold: data quality sets the performance ceiling for AI models, with multimodal datasets enabling precise decision-making (Brenna, Foiadelli, & Longo, 2016); V&V establishes the reliability floor, as rigorous validation fortifies system resilience against extreme scenarios. Both international academic research and industrial practice converge on the consensus that only through data-driven, lifecycle validation can safe and efficient railway autonomy be realized.

3.1 Train operation control and energy-efficient driving

The rationale for contextualizing train operation control and energy-efficient driving within a unified framework resides in their roles as both theoretically distinct and operationally intertwined core research domains in rail transit, each demonstrating intrinsic linkages to AI.

The core tasks of train operation control integrate train tracking interval management, speed protection (e.g. ATP systems), route planning and timetable enforcement, fundamentally forming a closed-loop control system that merges physical models (such as train dynamics equations) with regulatory constraints (such as signaling system protocols) (Albrecht, Howlett, Pudney, Vu, & Zhou, 2016a). Energy-efficient driving aims at minimizing energy consumption (e.g. electrical energy usage) or environmental impacts (e.g. carbon emissions) through optimizing train traction and braking behaviors, including traction levels, coasting timing and braking intensity, within the safety boundaries established by operation control, such as block section speed limits and tracking intervals (González-Gil, Palacin, & Batty, 2013). Energy-efficient driving functions as an optimization process under constraints imposed by operation control, with its solution space defined by parameters such as maximum allowable speed and minimum tracking interval. For example, in the ATO system, the operation control module generates a safe speed envelope, whereby the energy-efficient driving module identifies the optimal energy consumption trajectory through adaptive adjustment of traction and braking profiles (Gore, Dudhe, & Raina, 2023). A contradiction emerges, however: while traditional operation control adheres to the principles of safety-first and efficiency-primacy, the integration of energy-efficient driving disrupts the mono-objective optimization paradigm, giving rise to challenges in multi-objective coordination that require simultaneous optimization of safety, punctuality and energy sustainability (Zhang, Li, Yuan, & Yang, 2025). The safety boundaries of operation control, such as emergency braking distance, admit of no violation and energy-efficient driving optimization must be executed within these rigid constraints (Felez & Vaquero-Serrano, 2023). While shortening travel time typically necessitates higher average speeds and reduced coasting or braking instances, thereby inherently increasing energy consumption, extreme energy efficiency can be achieved through extended coasting distances (Kljaić *et al.*, 2023). However, this approach entails the risk of deviating from timetable constraints, such as the probability of delays.

Albrecht, Howlett, Pudney, Vu, and Zhou (2016b) pioneered a theoretical foundation for AI-based train control by establishing a local energy minimization principle and proving the existence of optimal train operation strategies. This work has not only provided a coherent synthesis of academic advancements in modern train control theory over the past three decades but also offered critical guidance for future research directions. Following this foundational work, numerous studies such as those by Luan *et al.* (2018), Farooqi, Fagiano, Colaneri, and Barlini (2020), Su, Wang, Tang, Wang, and Cao (2021) and Peng *et al.* (2025) have proposed and applied diverse methodologies, including mixed-integer nonlinear programming (MINLP), custom-developed models, innovative frameworks and nonlinear MPC, to investigate energy-efficient train operation strategies. Previous studies have also conducted specialized research on energy-efficient operation for trains in specific scenarios, including metro and urban rail trains (Yang, Li, Ning, & Tang, 2016), heavy-haul trains (Zhang, Xu, Fan, & Zhuan, 2012) and other dedicated applications. These extensive studies conducted thus far highlight the importance of the research subfield focusing on train operation control and energy-efficient driving within the broader domain of integrating AI with automatic train driving and control. While scholars have already made substantial contributions to this area, the field still exhibits considerable room for advancement and optimization, necessitating significant future research, especially as AI becomes increasingly intertwined with train automation technologies.

3.2 Scheduling optimization

In the realm of scheduling optimization, AI technologies have been predominantly applied in key scenarios such as dynamic timetable optimization, large-scale railway network conflict management, multi-objective energy-efficient scheduling, real-time delay recovery and crew scheduling. Typical AI techniques employed in these scenarios include particle swarm optimization (PSO), genetic algorithms (GA), fuzzy logic, deep reinforcement learning (DRL) and graph neural networks (GNNs), which collectively address the complexity of spatiotemporal constraints, dynamic demand fluctuations and multi-objective trade-offs inherent in modern rail systems (Liu, Liu, Wang, & Zhang, 2024). Over the past two decades, many studies, such as those by Li, Wei, and He (2011) and Yaman, Karakose, and Karakose (2018), have applied PSO technology to dynamic timetable optimization research, specifically focusing on reducing train waiting time and addressing online timetable re-scheduling challenges. In the evolution of technology and research, scholars have leveraged optimal/suboptimal solutions to address the multi-objective optimization problem of timetable rescheduling (Ding *et al.*, 2024), thereby streamlining workflows and enhancing the computational efficiency of AI-driven algorithms. Recent research efforts have integrated fuzzy logic with specific AI methodologies to enhance decision-making capabilities in railway traffic management and have demonstrated the effectiveness of fuzzy logic in handling railway traffic flow, reducing delays and improving passenger satisfaction (Kumari *et al.*, 2024).

In scheduling optimization, the crew scheduling problem (CSP) stands as one of the core challenges in railway operations, with the objective of optimally assigning crew members to predefined tasks while satisfying constraints such as safety regulations, work-hour limits and skill matching, all the while minimizing operational costs or maximizing service quality. As an NP-hard problem, CSP exhibits exponential complexity with respect to the number of tasks, though scholars have leveraged the modified bacterial foraging algorithm (BFA) to optimize crew scheduling (Pang & Chen, 2023), thereby demonstrating that AI offers robust solutions to such computationally intensive challenges.

3.3 Fault Diagnosis and Prognosis

AI-based Fault Diagnosis and Prognosis (FDP) has been extensively deployed in railway systems for the health management of critical components and subsystems, including wheelset and bearing systems, traction drive systems, on-board key equipment, and turnout and track infrastructure, with the core objective of achieving early fault identification, remaining useful life (RUL) prediction and maintenance strategy optimization through intelligent algorithms. In this paper, we primarily review FDP for wheelset and bearing systems, given their critical role in ensuring operational safety and their multifarious fault modes, such as wear, cracks, spalling and lubrication failure, which are primary contributors to abnormal train vibration and derailment. These faults can be further categorized into numerous subclasses. For example, wheelset failures encompass wheel flat, wheel build-up material and thermal-mechanical crack, while common surface defects in wheels include wheel polygonization and flange wear among others (Ye *et al.*, 2025). A study has proposed an experimental setup and model capable of emulating a near-realistic environment for high-speed railway wheelset bearing testing, with the objective of extending service life, and this has been widely referenced by subsequent academic research (Xu, Hou, Qi, & Bo, 2021). Yan, Chen, Bai, Yu, and Yu (2022) conducted a comprehensive review on fault diagnosis methods for rolling bearings of railway vehicles, encompassing multiple domains such as acoustic signal fault diagnosis and temperature prediction diagnosis methods, and proposed new research perspectives for future fault diagnosis methodologies and innovative system development, including fault diagnosis algorithm and integrated application, anti-interference processing and big data management application. Recently, a study has conducted an extensive review of extensive academic research on fault diagnosis methods for railway wheelsets, comparing the advantages and disadvantages of each method, which highlights the importance attached by practitioners to wheelset and bearing systems (Ye *et al.*, 2025).

Numerous other studies have addressed almost all components of railway systems: one study proposed an early fault diagnosis method for spur gears in railway gearboxes (Karpat *et al.*, 2020); another research developed a deep learning approach for fault detection in on-board equipment of high-speed trains (Yin & Zhao, 2016); another study employed qualitative approaches to diagnose faults in high-speed trains (Cheng *et al.*, 2021); and there were also investigations on turnout machines (Hu, Cao, Tang, & Sun, 2022) and traction system (Chen, Jiang, Ding, & Huang, 2022). Scholars in this critical field need to continue focusing on small-sample fault data augmentation, cross-modal feature fusion (e.g. acoustic-vibration-image), and the application compliance of explainable AI in safety-critical systems, so as to facilitate the transition of advanced technologies from laboratory to industrial-scale deployment.

3.4 Human–machine interaction

In railway systems, research on human-machine interaction (HMI) focuses on the information interaction mechanisms, collaborative decision-making logic and interface design optimization between humans (drivers and passengers) and machines (control systems) in intelligent train systems. As an interdisciplinary research direction, it aims to achieve bidirectional information transmission, intention comprehension and control authority coordination between humans and train control systems through sensor technology, interface engineering and intelligent algorithms. Due to the extensive applications of HMI in the transportation industry, some studies have reviewed the commonalities of HMI in railway and other sectors and proposed considerations on HMI comfort and future improvements (Enjalbert, Gandini, Pereda Baños, Ricci, & Vanderhaegen, 2021). Scholarly research on human comfort, trust and training in HMI is abundant: a study analyzes how human–machine collaboration is achieved in remote driving (Pacaux-Lemoine, Gadmer, & Richard, 2020); another study focuses on evaluation methods for human–machine trust in high-speed railways (Li, Liang, Niu, & Zhang, 2024a); one study proposes training assistance systems for HMI (Li, Chen, Luo, & Zheng, 2025); and another study investigates whether anthropomorphic interfaces can enhance ergonomics and safety performance in multi-task human–machine collaboration scenarios (Jiang & Zhi, 2025).

In recent research, Sobrie and Verschelde (2024) proposed a decision support system to enhance the proactive management of HMI in safety-critical digital railway control rooms. Yong *et al.* (2025) conducted a study that proposed multiscale feature detection for AR assembly objects, achieving virtual-real fusion registration applications in rail transit AR human–machine collaborative assembly, an important contribution to the digital transformation phase of Industry 5.0. And based on the extensive research discussed above, we contend that future studies can optimize HMI, a pivotal technology for the transition of intelligent trains from assisted to fully autonomous driving, through approaches such as interdisciplinary collaboration (e.g. neuroscience and control engineering), and by concentrating on technologies including robust interaction mechanisms in dynamic environments and bidirectional quantitative modeling of human–machine trust.

3.5 Predictive maintenance

Historically viewed as a mere necessity to sustain system operation with little focus on strategies due to machines' inherent need for periodic repair/replacement, maintenance has drastically evolved to prioritize availability, cost minimization and resource optimization in modern practices (Binder, Mezhuyev, & Tschandl, 2023). A 2019 article provided a systematic review of machine learning (ML) techniques applied to PM, where ML, as a subset of AI, has been widely adopted in PM due to its capability to handle high-dimensional and multivariate data and extract hidden relationships within complex dynamic environments (Carvalho *et al.*, 2019). This pivotal article, widely cited in academia, has also provided critical support for subsequent research and served as a bridge between past and future studies. From key articles discussing ML technology in PM from a decade ago (e.g. Li *et al.*, 2014) to relevant articles within the past five years (e.g. Putra, Supangkat, Nugraha, Hidayat, & Kereta, 2021), we anticipate that ML applied to PM will continue to be widely researched in the future. Additionally, H-Nia, Flodin, Casanueva, Asplund, and Stichel (2024) argue that integrating PM with Digital Twins (DT) is highly promising, noting that current research in the railway industry regarding this integration remains scarce. We concur with this perspective, as DT serves as a powerful tool, and thus intend to discuss DT technology in the further directions section of this paper.

3.6 Safety and cybersecurity

Numerous academic literature have extensively explored the security and cybersecurity issues of AI technologies applied to railway systems (e.g. Oh *et al.*, 2022; Hadj-Mabrouk, 2024; Mihail & Bulgariu, 2024; Soderi, Masti, & Lun, 2023b and their references). In the field of autonomous train driving and control, AI technologies are quite widely used in Safety and Cybersecurity, including AI-based intrusion detection systems (IDS) utilizing Convolutional Neural Networks (CNN) and GNNs, as well as Driver Monitoring Systems (DMS) that assist drivers or maintenance personnel in enhancing safety decision-making efficiency and reducing risks of human operational errors. Notably, the safety of the signaling system is of utmost importance, as it encompasses all equipment required to ensure the safe operation of trains on railway infrastructure and fulfills several essential roles in maintaining safe and efficient railway services (Soderi, Masti, Hämäläinen, & Iinatti, 2023a). Schlehuber, Heinrich, Vateva-Gurova, Katzenbeisser, and Suri (2017) and Ji, Wang, Liu, and Liu (2025b) respectively discussed the shell concept for railway signal safety and the cloud computing-based dual-machine hot standby system technology, with the time span and research directions of these two literature reflecting the technological development and research heat in this field.

In 2024, an influential study delved into the cybersecurity measures employed by railway systems and the threat vulnerabilities they face, analyzing multiple cases of cyberattacks or threats targeting national railways, including the 2017 Deutsche Bahn Ransomware Attack, the 2022 Ukrainian Railway Cyberattacks and the 2022 Trenitalia Ransomware Attack, and proposed a layered security framework as a solution (Ibadah, Benavente-Peces, & Pahl, 2024). It is evident that cybersecurity vulnerabilities continue to persist across railway networks worldwide, and integrating AI technologies such as GNNs into cybersecurity research for application in solutions holds significant potential. Another study critically compared AI technologies with traditional techniques, concluding that traditional methods struggle to dynamically detect anomalies and adapt to dynamic network environments due to the lack of Situation Awareness (SA) (Li & Wang, 2023). Currently, the continuous increase in train speed has given rise to greater accident risks, while the development of various smart train control systems that enhance the intelligence of train operation control has also increased system complexity and made control tasks more intricate (Zamouche, Aissani, Omar, & Saad, 2022). Thus, leveraging advancing AI technologies to address the increasingly complex safety and cybersecurity challenges represents a promising solution.

4. Future directions

In this section, we systematically summarize nine high-potential technologies or future research directions in the field of integrating AI technology with train driving and control. These nine items, which respectively belong to different technical tiers, methodological categories or application dimensions, exhibit independence in academic scopes, technical principles and core functionalities, covering not only core technological breakthrough directions of AI in train driving and control but also cutting-edge interdisciplinary fields such as ethics, standardization, as well as frontier technologies in the early exploration stages. We argue that through continuous algorithm optimization and technological upgrading in individual or specific domains, coupled with sustained attempts at interdisciplinary research approaches, intelligent train control will continue to make new advancements.

4.1 Digital twin

The concept of DT was first proposed by Michael Grieves from the University of Michigan in 2002, but gained broader research attention starting from 2016, initially applied to Product

Lifecycle Management (PLM) before being practically promoted by NASA in the aerospace sector (Singh *et al.*, 2021). As a technology system that dynamically maps physical entities or systems through real-time data-driven virtual models to support prediction, optimization and decision-making (Liu, Fang, Dong, & Xu, 2021). DT has only begun to be applied in the railway domain in recent years, with related research showing a sustained upward trend, specifically from only a few studies across the railway domain in 2017 to nearly a thousand by 2022 (Krmac & Djordjevic, 2024). A recent study published in late 2024 reviews the applications of DT in rail, indicating that it currently provides innovative solutions primarily for improving operational efficiency, safety and predictive maintenance (Kushwaha, Kumar, & Harsha, 2024). However, we contend that DT research in train driving and control remains in its infancy, with related studies still relatively scarce. Our perspectives on future research directions and suggestions for scholars include: leveraging Diffusion Models to generate data for extreme scenarios such as earthquakes and typhoons to enhance the generalization capability of DT; deeply integrating DT with edge intelligence to deploy lightweight DT models to in-vehicle edge nodes for localized real-time decision-making; and establishing cross-vendor DT data interface standards to address model compatibility issues across different railway lines and train types.

4.2 Edge computing

With the development of the Internet of Things (IoT) and the promotion of 4G/5G, as well as the demand to overcome bottlenecks such as slow response speed, poor security and privacy issues in cloud computing, Edge computing (EC), recognized as one of the key technologies for next-generation communication networks, has emerged (Cao, Liu, Meng, & Sun, 2020). EC is a computing model that provides intelligent services near the network edge by sinking data processing, storage, application services and other capabilities to edge nodes, meeting the critical needs of industry digitization in terms of agile connectivity, real-time operations, data optimization, security and privacy protection (Shi, Cao, Zhang, Li, & Xu, 2016). In train driving and control, EC specifically refers to a distributed computing architecture composed of in-vehicle terminals, roadside devices (such as signal machines and base stations) and edge data centers, which supports localized real-time decision-making of AI algorithms (Zhu, Liang, & Li, 2024a). Additionally, one study also proposes using EC to detect obstacles and obtain the distance between trains and obstacles, thereby optimizing autonomous train driving (Gong & Zhu, 2022). However, the application of this new AI technology in this field still has enormous potential for improvement, for example, whether it is possible to develop a dedicated AI chip for edge devices to support dynamic network adaptation and precision adjustment, enabling in-vehicle edge nodes to simultaneously handle multiple tasks such as environmental perception, path planning and equipment status monitoring. Based on an analysis of current research and applications, we argue that constructing a 6G EC prototype and leveraging 5G-A's (eMBB) and 6G terahertz communications to build a three-tier collaborative architecture of in-vehicle edge, roadside edge, and regional cloud represents a direction of high research value.

4.3 Virtual coupling

Virtual coupling (VC), a highly innovative concept in the future railway domain, adds to the ATC system the functionality of virtually connecting multiple trains, thereby reducing headways and enhancing line capacity, and enabling intelligent upgrades to traditional physical train marshalling (Flammini *et al.*, 2018). In fact, VC technology not only adjusts real-time train spacing but also brings benefits such as reduced operational and maintenance costs, lower energy consumption and increased sustainability. Felez and Vaquero-Serrano (2023) conducted a comprehensive review of 200 papers on VC applications in rail, identifying key future research directions for VC, including complete dynamic models, real-time controllers, different communication topologies, intelligent control and Big Data analytics, among others. This demonstrates the critical role and high research value of VC. Recently, we have also noted a creative new study that, to address the train safety spacing issue in VC, proposes a model based on the artificial potential field (APF) method for safely monitoring the complete braking process of trains in VC queues, with existing application cases (Ji, Quaglietta, Goverde, & Ou, 2025a). We argue that such technological updates bring safety, convenience, and well-being to people's travel. Going forward, we believe VC research can build on its existing advantages and continue to focus on improving transportation efficiency, particularly for marshalling during peak commuting hours and in high-traffic sections, while optimizing the Life Cycle Cost (LCC) of VC systems through integration with Life Cycle Assessment (LCA) models.

4.4 Federated learning

Data serve as the foundation of the AI field, yet it often exists in the form of data silos, and traditional data processing methods suffer from multiple drawbacks such as poor privacy protection (Zhang *et al.*, 2021). As a result, federated learning (FL) has been proposed as a new machine learning model training paradigm. First introduced by Google in 2016, FL was initially used for localized model updates in Android mobile phone input methods to address user privacy protection and data silo issues (Li, Fan, Tse, & Lin, 2020). In the railway domain, FL is in the early stages of application, initially employed to train fault diagnosis models by integrating maintenance data from different railway companies, as seen in the studies by Qin, Du, Zhang, Huang, and Wu (2023) and Wen, Chen, Zhang, Roberts, and Cai (2024). Although FL is frequently used as an effective solution for protecting privacy-sensitive data, Zhu *et al.* (2024b) creatively explored its limitations, demonstrated the attack threats it faces and proposed solutions. Therefore, when envisioning the future applications of FL in train autonomous driving and control, our focus primarily lies in its potential for fault diagnosis and reducing maintenance costs of critical components, for example, optimizing maintenance cycles by jointly using in-vehicle sensor data and component lifespan data from suppliers.

4.5 Quantum computing

This paper argues that quantum computing (QC) holds enormous potential for applications in the railway domain, particularly in autonomous driving and control. QC is poised to become a disruptive technology, with the Chinese government investing $10 billion in establishing a national QC laboratory, the United States allocating a $1 billion budget and the European Union exceeding €1 billion (Rietsche *et al.*, 2022). QC's unparalleled computational power is exemplified by a quantum computer built by Chinese scientists in 2020, which performed specific calculations 100 trillion times faster than the world's most advanced supercomputer at the time (Zhong *et al.*, 2020). Despite its enormous advantages, industrial applications of this technology remain extremely limited so far. A profound 2025 study discusses the significance, prospects and potential applications of QC in the Industry 4.0 era, asserting that it can fundamentally transform operational modes across industries (Jami & Haleem, 2025).

We contend that it will also emerge as a breakthrough technology in rail, though current applications are scarce, confined to a few studies on quantum annealing, such as those by Domino *et al.* (2023) and Qin, Guo, Xu, Li, and Wang (2025). We propose that research over the next 5–10 years can primarily focus on three directions: first, applying quantum annealing algorithms to train timetable optimization and progressively implementing them after demonstrating effectiveness; second, researching and deploying Quantum Key Distribution (QKD) systems to enable encrypted communication between in-vehicle signal systems and ground equipment; third, developing quantum EC devices by designing low-power chips fusing quantum and classical technologies, for example, a railway-customized version of Intel's Horse Ridge quantum control chip, with the ultimate goal of commercializing quantum chips in autonomous driving controllers following validation trials.

4.6 Vehicle–road–cloud collaboration

The concept of vehicle–road–cloud collaboration originates from the “human–vehicle–road–environment” collaborative philosophy in intelligent transportation systems (ITS), which is inherently linked to communication and real-time data. In this paper, we identify vehicle–road–cloud collaboration as one of the future research directions in intelligent train control because we have observed the progress of this concept in the automotive sector and believe it can achieve similar success in railways. Studies have discussed the challenges brought by the continuous development of 5G/6G and AI, such as the accuracy of channel estimation in high-speed mobile environments and edge collaborative optimization, which bring both opportunities and challenges for railway wireless communication systems (Zhao, Gao, Wu, Zhang, & Han, 2024). Other research has envisioned the vision of enhancing train operation safety, efficiency and reliability through 6G applications in high-speed railways (Chen *et al.*, 2025). We believe that with the advancement of communication technologies, vehicle–road–cloud collaboration will drive significant breakthroughs in areas such as train fleet operation scheduling strategies, obstacle detection and shortening emergency braking distances. In the future, practitioners and researchers can focus on the technological symbiosis and collaborative development among vehicle–road–cloud collaboration, DT, EC and VC to make new contributions to the advancement of intelligent train control.

4.7 Generative AI

In this subsection, this paper presents our high expectations and research perspectives on the prospects of generative AI, aiming to provide actionable insights for practitioners and researchers in related fields. For those interested in generative AI and models/technologies applying generative AI represented by ChatGPT, please refer to Feuerriegel, Hartmann, Janiesch, and Zschech (2024) and Fui-Hoon Nah, Zheng, Cai, Siau, and Chen (2023). Based on our existing knowledge in the railway domain, this paper argues that: generative AI can be used to synthesize high-fidelity simulated extreme scenario data such as derailments and signal failures, which are difficult to obtain through real-vehicle testing, and increase the training data volume by several times, thereby solving the problem of data scarcity; after deeply integrating generative AI with industry large models, it can process cross-modal data (such as dispatching command text plus real-time sensor data) to achieve end-to-end conversion from “natural language instructions to control signals,” thereby improving the level of decision-making intelligence; generative AI can be used to automatically design new train control algorithms, such as generating lightweight CNN models through neural architecture search, thereby shortening the algorithm R&D cycle. We prospectively believe that, based on the current pace of technological development and the technologies currently mastered, the above aspects can all be achieved in the short term or further explored, while generative AI will play a broader role in the slightly more distant future.

4.8 Standardization system

In any industrial and technological domain, the establishment of a standardization system is indispensable. In the field discussed in this paper, scholars should establish or gradually improve the corresponding standardization systems for the various technologies mentioned herein, especially for newly applied technologies or facilities. Developing AI-related standardization systems poses challenges that require researchers to approach from diverse perspectives, with particular emphasis on standards related to human–machine collaboration, which should prioritize the people-oriented principle. Key focuses should include specifications or standardized assessment systems for passenger safety priority, AI system compliance decision-making rates in emergency scenarios, cross-vendor equipment compatibility and quantum algorithm verification (such as reliability metrics for quantum annealing scheduling models). From a long-term and more meaningful perspective, the incompatible AI control instruction formats between China’s CTCS and the EU’s ETCS increase the reconstruction costs of cross-border train autonomous driving systems. It remains to be explored whether there is a need to unify the standard formats through some means to better serve the potential launch of more China–Europe cross-border trains. In terms of implementation and application, solutions such as establishing a hierarchical framework covering basic commonality, supporting technology and scenario application to formulate general specifications for AI model development (such as data formats and interface protocols); refining reliability assessment indicators for cutting-edge technologies like GNNs and QC; and establishing a tripartite alliance consisting of railway operators, AI enterprises and standardization organizations to regularly update standards in adaptation to technological evolution will be promising and practical. It can be foreseen that the establishment of various AI-related standardization systems will become an important research and breakthrough direction in the future.

4.9 Ethical and safety

A study posits that AI Ethics constitutes a novel domain of applied ethics, with the European Commission releasing the "Ethics Guidelines for Trustworthy AI" in April 2019, the Institute of Electrical and Electronics Engineers (IEEE) publishing "Ethically Aligned Design" in 2017, and the Partnership on AI issuing the "AI Ethics Code" in 2022, all of which provide constructive guidance and references for AI Ethics (Perov & Golovkov, 2024). These documents also offer practically meaningful direction and assistance for the ethical standards in the domain of this paper. Ethical and safety issues are inherently intertwined, and the reliability and safety of AI systems have long been central research themes. A study critically evaluated articles on AI and safety in industrial research, concluding that while AI is increasingly employed to enhance occupational safety, there is an urgent need to address regulatory and ethical challenges (Huber *et al.*, 2025). For future directions, scholars should establish theoretical frameworks, technical methodologies and evaluation systems to ensure that AI system decisions align with human values, legal norms and functional safety standards, thereby effectively managing risks and addressing ethical and safety issues arising from the integration of AI with train driving and control.

5. Conclusion

This paper presents a comprehensive review of AI technologies applied to train driving and control, analyzing numerous cases and cutting-edge papers in the field. We exemplify and revisit six research directions where AI has been widely adopted: Train Operation Control, Scheduling Optimization, FDP, HMI, Predictive Maintenance and Cybersecurity. Furthermore, based on the analysis, this paper anticipates nine key AI technologies or research directions with high potential for future applications in train driving and control. It can be seen that emerging areas such as generative AI, QC for solving NP-hard scheduling problems and ethical frameworks for safety-critical decision-making will bring unprecedented opportunities to this domain. These technologies will help address unresolved issues like extreme environment robustness and vehicle–road–cloud integration. While these technologies and research directions offer opportunities, they are faced with numerous challenges. For instance, in safety-critical verification, ensuring AI decisions meet stringent safety standards (such as SIL 4 certification) remains a technical and regulatory challenge, requiring advancements in formal verification and adversarial testing. Additionally, regarding data heterogeneity, the railway system generates multi-source and multi-modal data such as sensor signals and maintenance logs, urgently demanding robust data fusion technologies and scalable infrastructure. Moreover, in terms of ethics and social acceptance, defining clear AI ethical guidelines for accident-prone scenarios (such as control handover triggered by failures) and building public trust in autonomous systems are critical for technology implementation. These challenges also provide directions for interdisciplinary research integrating computer science and ethics to develop holistic solutions.

From fundamental data processing, such as privacy-preserving FL to advanced decision-making technologies like system simulation DT, various AI techniques are reshaping railway operations and delivering significant improvements, as validated by the application of multi-objective RL to balance safety, energy efficiency and operation speed in high-speed rail. It can be foreseen from this paper that the future of train driving and control will be characterized by an increasing number of AI-based studies, with numerous unresolved research topics and directions expected to emerge to bridge existing research gaps. The limitation of this paper lies in that, due to the wide variety of AI technologies applicable to train driving and control and their rapid evolution, while this paper has selected key directions that the authors consider highly promising or showing preliminary progress after critical analysis, it may overlook potential technologies or application areas that have not yet demonstrated their potential. Overall, we recognize that AI research in train driving and control remains in its infancy but holds substantial potential. We anticipate that future academic studies will identify new problems solvable by AI technologies and continue to leverage emerging technologies to address existing issues. AI is set to bring unprecedented solutions, new opportunities and novel advancements.

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