High-speed Railway 2 (2024) 11–16

Contents lists available at ScienceDirect

High-speed Railway

journal homepage: www.keaipublishing.com/en/journals/high-speed-railway

Review article

A review of artificial intelligence applications in high-speed railway systems

Xuehan Li[a], Minghao Zhu[b], Boyang Zhang[a], Xiaoxuan Wang[a], Zha Liu[a], Liang Han[c,*]

[a] School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing 100044, China
[b] School of Economics and Management, Beijing Jiaotong University, Beijing 100044, China
[c] Business School of Hunan University, Changsha 410082, China

ARTICLE INFO

Keywords:
High-speed railway
Artificial intelligence
Intelligent distribution
Intelligent control
Intelligent scheduling

ABSTRACT

In recent years, the global surge of High-speed Railway (HSR) revolutionized ground transportation, providing secure, comfortable, and punctual services. The next-gen HSR, fueled by emerging services like video surveillance, emergency communication, and real-time scheduling, demands advanced capabilities in real-time perception, automated driving, and digitized services, which accelerate the integration and application of Artificial Intelligence (AI) in the HSR system. This paper first provides a brief overview of AI, covering its origin, evolution, and breakthrough applications. A comprehensive review is then given regarding the most advanced AI technologies and applications in three macro application domains of the HSR system: mechanical manufacturing and electrical control, communication and signal control, and transportation management. The literature is categorized and compared across nine application directions labeled as intelligent manufacturing of trains and key components, forecast of railroad maintenance, optimization of energy consumption in railroads and trains, communication security, communication dependability, channel modeling and estimation, passenger scheduling, traffic flow forecasting, high-speed railway smart platform. Finally, challenges associated with the application of AI are discussed, offering insights for future research directions.

1. Introduction

In recent years, the rapid ascent of environmentally sustainable, efficient, and cost-effective High-speed Railway (HSR) on a global scale has provided substantial convenience to society. Renowned for delivering secure, comfortable, and punctual passenger services comparable to air travel, HSR stands prominently as one of the most sustainable and promising advancements in ground transportation [1]. Compared with traditional HSR systems, the next generation of HSR system, driven by emerging services such as high-definition video surveillance, railway emergency communication, high reliability, low-latency internet access, and real-time train scheduling, imposes heightened requirements on aspects like real-time perception, automated driving, sustainable operation, networked systems and digitized services [2]. The above demands are the concrete manifestations of HSR intelligence in various branches. Accordingly, via the integration of cloud computing, the Internet of Things, big data and other new-generation information technologies, HSR intellectualization is currently the most forward-looking new stage in the development of HSR systems [3].

Artificial Intelligence (AI) has been defined as a system's capability to reasonably interpret external data, adapt and learn from the data, and employ the conclusions drawn from learning to achieve specific goals and tasks [4]. With the advancements in perception devices such as cameras and Light Detection and Ranging (LiDAR), the deployment of computational networks like cloud computing, fog computing, and edge computing, along with breakthroughs in communication technology represented by 5 G, contemporary AI not only has the capacity to learn from vast amounts of sensed data but can also emulate biological processes for autonomous reasoning and self-improvement [5]. The formidable deductive capabilities and scene generality of AI make it a crucial means of addressing key challenges in virtually every domain within academia and industry [6]. In the context of HSR systems, AI technology holds promise for application in areas such as vehicle manufacturing, railway infrastructure planning, power supply, channel estimation, signal control, and trafficprediction. The applications significantly enhance the efficiency of manufacturing, distribution, communication, and transportation, while ensuring the safety of railways, trains, passengers, and operations.

* Corresponding author.
E-mail address: leonhan@hnu.edu.cn (L. Han).

https://doi.org/10.1016/j.hspr.2024.01.002
Received 12 December 2023; Received in revised form 19 January 2024; Accepted 26 January 2024
Available online 29 January 2024

In this survey, based on a brief introduction to AI, we conduct a detailed integration and analysis of AI applications in the HSR system. Specifically, according to the different domains and functionalities of the applications, we categorize the surveyed works in a hierarchical structure and compare the details of their similarities and differences. Subsequently, we discuss several challenges associated with the application of AI in the HSR system. The purpose of this comprehensive review is to summarize the extensive applications of AI in the HSR system. We aim to provide readers with a fundamental understanding of the domains, functionalities, and prospects of AI applications in the HSR system through the integrated analysis of cutting-edge research. At the same time, the discussion of the challenges arising from the application of AI in this review will provide insights for future investigation. The remainder of this paper is organized as follows. Section 2 briefly overviews the origins, development and key breakthroughs of AI. In Section 3, we provide an in-depth exploration of the application of AI in the HSR system across three macroscopic domains—mechanical manufacturing and electrical control, communication and signal control, transportation management—and delve into nine specific directions: intelligent manufacturing of trains and key components, forecast of railroad maintenance, optimization of energy consumption in railroads and trains, communication security, communication dependability, channel modeling and estimation, passenger scheduling, traffic flow forecasting, highspeed railway smart platform. Section 4 delineates the challenges posed by the application of AI in the HSR system. Finally, some conclusions are made in Section 5.

2. Overview of AI

AI, as an important driving force of the new round of technological and industrial revolution, is playing an indispensable role in economic development, social progress and people's lives. Since the focus of this paper is to study the impact of artificial intelligence on HSR, we start first by making a brief overview of AI.

2.1. The origin and evolution of AI

AI is the subject of how to make machines simulate and learn intelligent tasks that can only be performed by humans. Although AI has gained extremely extensive study in recent years, it is not a new concept. The background of AI can be dated back to the 1940s and its development can be roughly divided into four stages. The two decades between 1940 and 1960 are the infancy of AI. Specifically, Warren McCulloch and Walter Pitts transformed the abstract neuronin biology into a simple mathematical model in 1943. In 1950, the architecture of the modern computer was proposed by John von Neumann and in the same year, Alan Turing proposed the famous Turing Test [7], which is a basic method for assessing whether a machine is intelligent or not, laying a good foundation for the development of AI. The concept of "artificial intelligence" was officially proposed by John McCarthy at the Dartmouth Conference in 1956 [8], marking the birth of AI. Ever since the concept of "artificial intelligence" was introduced in 1956, it has received a great deal of attention from academia as well as industry. From then on, AI really began to develop. The second stage is the first decade after AI was proposed, i.e., 1960–1970, which is the beginning stage of AI. Typical achievement in this phase is the Eliza computer program developed by Joseph Weizenbaum in 1966, which is a natural language processing system that can mimic a conversation with a human [7]. The third stage is from 1980 to 2000, which is a critical period in the development of AI. During this stage many academic groups made outstanding contributions to the development of AI. In 1983, Hayes Roth proposed the expert system which is a kind of intelligent computer program with specialized knowledge and experience. In the 1990s, neural networks and machine learning developed rapidly, laying the foundation for the further development of AI. Another landmark event in this stage is the defeat of world chess champion Garry Kasparov by IBM's Deep Blue supercomputer in 1997, which sparked a new wave of widespread interest in AI. From 2000 to today is the fourth stage in the development of AI, during which AI reaches its peak period. In 2012, deep learning was proposed, leading to a breakthrough development in AI [9]. In 2016, Google's AlphaGo defeated world champion Lee Sedol, which caused a huge stir in the AI community. In 2021, DeepMind's AlphaFold successfully solved the protein folding problem, meaning that AI can perform life's tasks. In 2020, OpenAI released GPT-3, which provides users with an intuitive interface for conservation with AI, realizing the innate human ability to communicate with others.

2.2. The origin and genesis of AI in HSR

With a history of almost 70 years, AI has played an important role in all industries, and the high-speed railway system is not excluded. AI first appeared in HSR around 2010 when a small group of researchers began exploring the concept of "intelligent high-speed railway". Fuzzy neural network is used to control the high-speed train travel process in Refs. [10,11]. After several years of exploration, the application of AI in HSR gradually matured and reached its heyday around 2017, which could be defined as the *Genesis* of AI in HSR. Some representative literature proliferated at this time. Least Squares Support Vector Machine (LSSVM) is used as a tool to analyze the position report generated from high-speed trains in Ref. [12]. A deep learning method is adapted to establish an automatic diagnostic network of vehicle onboard equipment for high-speed trains [13]. An AI-driven framework for high-speed railway prognostics and health management is presented in Ref. [14]. Through advanced signal processing and machine learning, the cyber-twin monitors real-time performance and predicts potential failures to prevent unplanned downtime and support optimization decisions. The application of AI in HSR highlights its significant potential in enhancing system safety, passenger comfort, and scheduling flexibility. This has provided positive feedback for the further integration of AI with HSR systems. However, with the deepening integration, some issues and challenges have gradually surfaced.

3. Applications of AI techniques in high-speed railway system

After thoroughly learning the trend of HSR and the development of AI, it is foreseeable that the integration of HSR and AI has potential. In this section, we introduce the application of AI techniques in HSR systems, including mechanical and electrical systems, communication and signal control and transportation management. The detailed structure of this section is presented in Fig. 1.

3.1. Mechanical manufacturing and electrical control

HSR is an integration of complex physical subsystems, such as train components, railroad tracks and electrical power systems, which all require delicate design and research. AI, as one of the very reliable analytical tools, provides strong support to the above aspects. Next, we will introduce the application of AI in mechanical and electrical systems from the following three perspectives, that are intelligent manufacturing of trains and key components, forecast of railroad maintenance, and optimization of energy consumption in railroads and trains.

3.1.1. Intelligent manufacturing of trains and key components

For HSR, the construction of the train is a matter of operational safety as well as speed enhancement. The reason for this is that the train bogie provides the train with steering assistance, keeps it on the rails and provides braking assis tance. Cheng et al. [15] designed a fault detection algorithm based on the improved Kalman filter while considering the performance degradation. They make a step further in running reliability and safety of HSR. Qin et al. [16] proposed an improved federated learning algorithm that established a bogie fault detection model while achieving data privacy protection. Yu et al. [17]

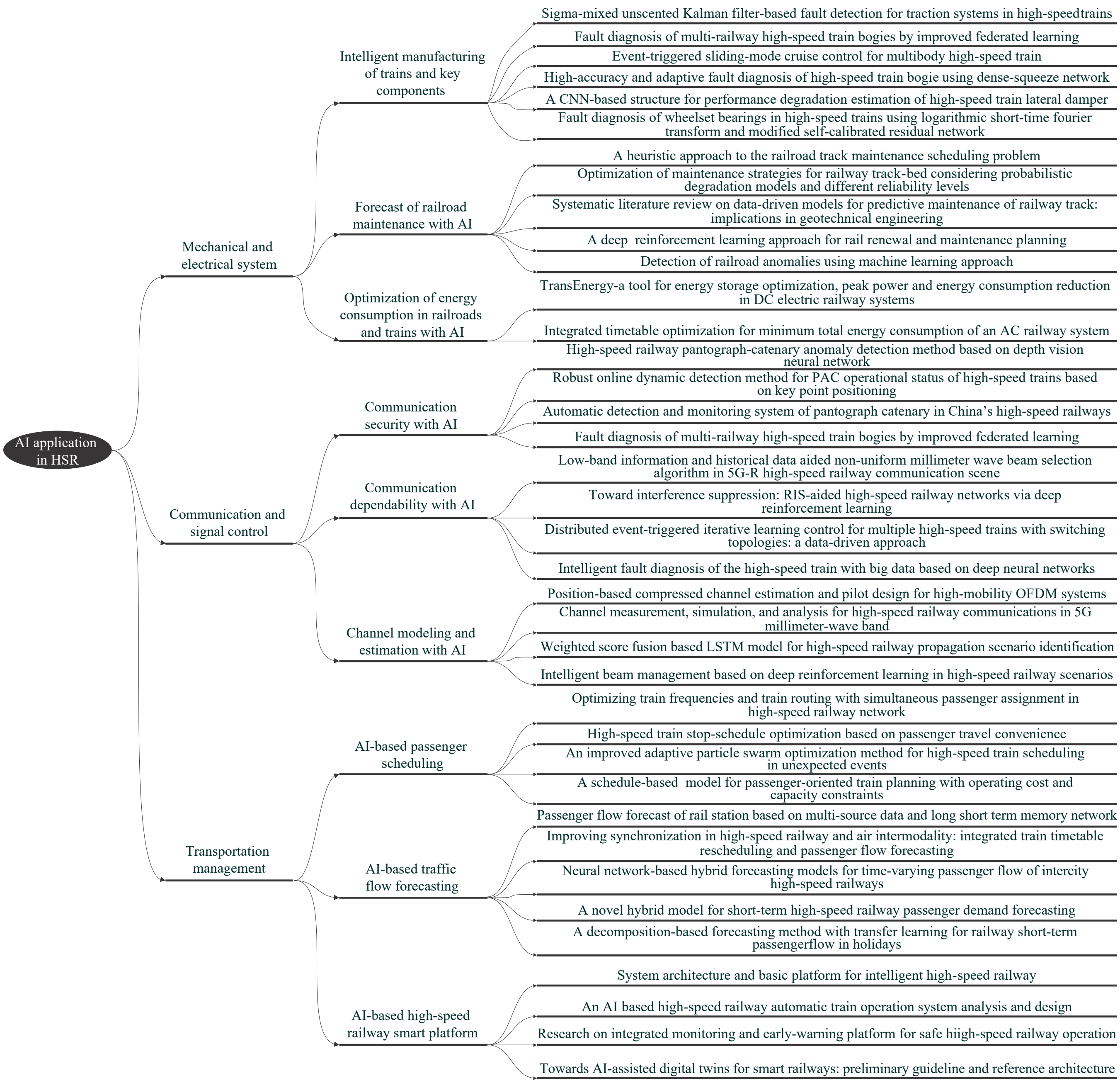

Fig. 1. The classification results of AI applications in HSR system.

studied a sliding-mode control aiming at multibody HSR. Considering the time-varying nature of the operating resistance in this paper, the error equation of the multibody HSR is modeled. Zhang et al. [18] proposed a novel Dense-Squeeze network based on a One-Dimensional Convolutional Neural Network (1D-CNN) for bogie fault diagnosis. This network enhances feature propagation and mitigates the gradient vanishing problem in deep learning network training. Xin et al. [19] proposed a new framework using the logarithmic short-time Fourier transform and a modified self-calibrating convolution for fault diagnosis of wheelset bearings in HSR. Ren et al. [20] explored the problem of estimating the performance degradation of lateral dampers for high-speed trains based on SDS-CNN.

3.1.2. Forecast of railroad maintenance

In addition to bogie design, the aspect of railway track maintenance is equally crucial, as it relates to the safe and efficient operation of the railway system. Peng et al. [21] proposed a time-space network model for solving the Track Maintenance Scheduling Problem (TMSP), which is solved through an iterative heuristic solution method. Nugraha et al. [22] stated that the railway anomaly detection process can be completed by using machine learning to compare the lateral, longitudinal and vertical accelerations derived from the sensing results of the accelerometers on both sides of the train wheels. Mohammadi et al. [23] optimised renewal and state-based maintenance schedules over the planning period by a deep reinforcement learning approach. Bressi et al. [24] proposed a Genetic Algorithm based methodology to minimise the present value of life-cycle maintenance costs and to maximise the level of life-cycle quality of the rail bed, taking into account different levels of reliability. Xie et al. [25] presented a systematic literature review of data-driven models applied to predictive maintenance of railway tracks, which is categorised according to model type and application type.

3.1.3. Optimization of energy consumption in railroads and trains

Last but not least, energy consumption is also important in the HSR system. A simplified alternating current traction system consists of a power transmission system, a catenary and a positive feeder line. Pan et al. [26] aimed to develop an integrated Genetic Algorithm based model to optimise the integrated timetable, which includes both the timetable and the train track, to achieve the lowest energy consumption. Fletcher et al. [27] created a Genetic Algorithm based model that combines a generic railway network model with a power supply network representing a DC electric railway that is database driven, versatile and configurable.

3.2. Communication and signal control

Communication and signal control play a vital role in HSR, and AI-enabled communication and signal control capabilities make it possible to increase the speed of trains. Therefore this subsection will introduce the application of AI in communication and signal control in the following three aspects, namely communication security with AI, communication dependability with AI and channel modeling and estimation with AI.

3.2.1. Communication security

With the rapid development of HSR technology, AI technology plays a crucial role in handling the encryption, monitoring, and analysis of communication data. Qin et al. [28] proposed an improved federated learning algorithm to build a global steering rack fault diagnosis model while protecting data security and privacy. The automatic detection and monitoring system in China's HSR is studied in Ref. [29]. The system is able to detect potential hidden dangers of the equipment in time, so as to effectively ensure the communication safety. Chen et al. [30] effectively identified and monitored critical features in pantograph-catenary system for communication security through a deep pantograph detection network and animage vision feature extraction algorithm. Ref. [31] propose a dynamic monitoring method to ensure a safe HSR operation.

3.2.2. Communication dependability

By integrating advanced AI algorithms and technologies, the HSR communication system can significantly improve the stability of the communication system through advanced data analysis, pattern recognition and automated decision support. Hu et al. [32] developed an accurate identification method for six failure scenarios of steering racks employing big data analysis with self-learning deep neural networks. Ref. [33] proposed a non-uniform beam selection algorithm based on low frequency bands and historical data which improves the stability of the HSR systems. Combining RIS and HSR can effectively enhance the network's immunity to interference [34]. Yu et al. [35] studied the distributed data-driven event-triggered model free adaptive iterative learning control of multiple high-speed trains operating under iteration-varying topologies, and proving its bounded input bounded output stability.

3.2.3. Channel modeling and estimation

AI utilizes sophisticated algorithms and cognitive mimicry techniques in order to automate and optimize the channel modeling and estimation process, which can significantly improve the performance of HSR communication systems. Ref. [36] propose a channel model for different scenarios by performing extensive ray tracing simulations in different high-speed railroad environments. In Ref. [37], a position-based HSR channel model is presented to reduce the estimation complexity. Deep reinforcement learning algorithms provide new solutions for beam management in high-speed moving sce-narios, realizing a trade-off between performance and train-ing overhead [38]. Zhou et al. [39] proposed a novel propagation scene recognition model that can effectively improve the performance of HSR communication networks.

3.3. Transportation management

Transport management is of significant importance in today's HSR research as it allows the whole system to become more efficient. The management system runs through the design phase, construction phase and operation phase. In previous analyses, AI-related technologies have performed well in these areas. In this subsection, the application of AI in transport management is described, which includes AI-based passenger scheduling, AI-based traffic flow forecasting and AI-based HSR smart platform.

3.3.1. Passenger scheduling

Passenger scheduling is of great research importance intransportation management as it relates to the passenger experience and the smooth operation of the entire railway system. Xie et al. [40] proposed a heuristic algorithm based optimization model which pays attention to timetabling and train unit scheduling, while also taking passenger trip selection into consideration. Li et al. [41] developed a bi-level multi-objective mixed-integer nonlinear programming model for simultaneously obtaining optimal solutions for passenger assignment and train routing. The results are obtained by swarm approach. Chen et al. [42] proposed a hybrid genetic algorithm to solve the established multi-target optimization model which aims at minimizing stop cost and maximizing passenger travel convenience in high-speed train scenario. Liu et al. [43] investigated an optimization scheduling scheme for high-speed trains to reduce total delay time and energy consumption under the circumstance of unexpected events.

3.3.2. Traffic flow forecasting

Short-term railway traffic forecasts play a crucial role for HSR companies and are the basis for ticket allocation, route planning and passenger station management. Wen et al. [44] improved the accuracy of short-term passenger flow forecasting for high-speed railways and overcame the traffic congestion challenge of holidays. A migration learning approach with time series decomposition is used. Zhao et al. [45] proposed a novel hybrid model combining the singular spectrum analysis, convolution neural network as well as support machine regression for forecasting the short-term HSR passenger demand. Zhang et al. [46] proposed a new method based on multilayer LSTM that integrates multi-source traffic data and multiple techniques (including feature selection based on Spearman correlation and temporal feature clustering). Tan et al. [47] focused on the HSR-Air Timetable Coordination (HATC) problem, and proposed a Genetic Algorithm to solve it. Su et al. [48] proposed three neural network-based hybrid forecasting models to predict the Origin-Destination (O-D) passenger flow at different times of the day.

3.3.3. High-speed railway smart platform

The smart platform is indispensable for railway operation and maintenance, traffic control, as well as for passenger arrival reminders and remote ticketing. De Donato et al. [49] investigated the utilization of digital twins in the railway sector, with a particular focus on the role of AI as a key enabler for building value-added services and applications related to intelligent decision-making. Li et al. [50] defined intelligent HSR and gave its connotation, which greatly accelerated the system architecture of HSR. The effort is significant in HSR platform development. Zhang et al. [51] proposed new ideas for improving the performance of HSR control systems using AI such as deep reinforcement learning and imitation learning, while presenting the objectives, structure and development process of the system. Xiao et al. [52] proposed a visual, intelligent and integrated monitoring and early-warning platform for safe high-speed railway operation.

4. Challenges

In exploring the use of human AI in HSR, we not only see the potential benefits, but must also face a number of challenges. This Section will delve into these challenges and discuss possible solutions and progress.

4.1. Data security and privacy

Data security and privacy protection become dual challenges when applying AI in HSR systems. With a large amount of sensitive data being collected and analyzed, including passenger information, operational data, and maintenance records, leakage or unauthorized access to this data can lead to serious privacy violations and security risks. To address these challenges, it is not only necessary to strengthen data encryption technologies, implement strict data access controls and continuously monitor data flows, but it is also essential to ensure that AI systems are designed to respect and protect individual privacy. This includes adhering to data protection regulations such as the European Union's General Data Protection Regulation (GDPR), as well as implementing principles of data anonymization and minimization of processing, so that system efficiency and functionality can be improved while ensuring that data security and individual privacy are adequately protected. There are many studies addressing security and privacy issues. In Ref. [53], the channel capacity of the eavesdropper can be guaranteed to be within a controllable range by jointly optimizing the beamforming vector and the discrete phase shift of the RIS. Wang et al. [54] proposed a proxy signature-based authentication scheme that can enhance the security of LTE-R without sacrificing efficiency. The use of federated learning in bogie fault diagnosis enables global modeling of bogie fault diagnosis while protecting the security and privacy of bogie data.

4.2. Algorithmic bias and social responsibility

AI algorithm bias may impact HSR in the following ways. Firstly, AI algorithm bias may lead to the neglect of certain safety hazards, such as insufficient recognition of specific types of failure modes, which can increase the risk of accidents; secondly, algorithm bias may lead to the misjudgment of certain maintenance needs or an unfair allocation of operational efficiencies, such as certain routes or vehicles receiving more frequent maintenance and optimization while others are neglected; thirdly, AI is used to optimize fares and plan routes when bias may result in certain areas or populations being treated unfairly, such as high fares or inconvenient routes; and fourthly, AI algorithms often rely on large amounts of data. If there is bias in data collection, such as over-emphasis on certain regions or types of data, this can affect the overall fairness and accuracy of the algorithm. On the other hand, the decision-making process for AI needs to take into account social responsibility. When deploying AI in HSR systems, the relationship between technological efficiency and social equity should be weighed. For example, when designing fares and services, AI systems should take into account the needs of passengers from different socioeconomic backgrounds to ensure the universality and fairness of services.

5. Conclusion

This paper provides a comprehensive review of popular application directions and start-of-the-art papers on artificial intelligence in the HSR systems. Unlike published reviews, we begin with a brief overview of the origins, evolution, and landmark achievements of AI, revealing the roots of the reasons that AI can be applied organically in the HSR system. From the macro perspectives of mechanical manufacturing and electrical control, communication and signal control, and transportation management, the current applications of AI in the HSR system are subdivided into nine sub-directions: intelligent manufacturing of trains and key components, forecast of railroad maintenance, optimization of energy consumption in railroads and trains, communication security, communication dependability, channel modeling and estimation, passenger scheduling, traffic flow forecasting, high-speed railway smart platform. These sub-directions represent the current focus and hotspots of research. Finally, we discuss issues and challenges to further advance and refine the application of AI in the HSR system. This discussion aims to contribute to future research by addressing current gaps and open areas in the field.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (62172033).

References

[1] B. Ai, X. Cheng, T. Kürner, et al., Challenges toward wireless communications for high-speed railway, IEEE Trans. Intel. Transp. Syst. 15 (5) (2014) 2143–2158.
[2] J. Calle-Sánchez, M. Molina-García, J. Alonso, et al., Long term evolution in high speed railway environments: feasibility and challenges, Bell Labs Tech. J. 18 (2) (2013) 237–253.
[3] T. Zhou, Y. Yang, L. Liu, et al., A dynamic 3-D wideband gbsm for cooperative massive mimo channels in intelligent high-speed railway communication systems. IEEE Trans. Wire. Commun. 20 (4) (2020) 2237–2250.
[4] A. Kaplan, M. Haenlein, Siri, siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence, Bus. Horiz. 62 (1) (2019) 15–25.
[5] Y. Lu, Artificial intelligence: a survey on evolution, models, applications and future trends, J. Manag. Anal. 6 (1) (2019) 1–29.
[6] J. Zhang, D. Tao, Empowering things with intelligence: a survey of the progress, challenges, and opportunities in artificial intelligence of things, IEEE Int. Things J. 8 (10) (2020) 7789–7817.
[7] Q. Tang, F.R. Yu, R. Xie, et al., Internet of intelligence: a survey on the enabling technologies, applications, and challenges, IEEE Commun. Surv. Tutor. 24 (3) (2022) 1394–1434.
[8] E. Baccour, N. Mhaisen, A.A. Abdellatif, et al., Pervasive aiforiot applications: a survey on resource-efficient distributed artificial intelligence. IEEE Commun. Surv. Tutor. 24 (4) (2022) 2366–2418.
[9] D.C. Nguyen, P. Cheng, M. Ding, et al., Enabling AI in future wireless networks: a data life cycle perspective. IEEE Commun. Surv. Tutor. 23 (1) (2021) 553–595.
[10] J. Yu, Q.Q. Qian, Z. He. Research on application of two-degree fuzzy neural network in ATO of high speed train. J. China Railw. Soc. 30 (10) (2008) 52–56.
[11] X. Tao, Adaptive fuzzy control of train operation, J. China Railw. Soc. 4 (2010) 44–49.
[12] R. Cheng, Y. Song, D. Chen, et al., Intelligent localization of a high-speed train using lssvm and the on- line sparse optimization approach, IEEE Trans. Intel. Transp. Syst. 18 (8) (2017) 2071–2084.
[13] J. Yin, W. Zhao, Fault diagnosis network design for vehicle on-board equipments of high-speed railway: a deep learning approach. Eng. Appl. Artif. Intel. 56 (2016) 250–259.
[14] Z. Liu, C. Jin, W. Jin, et al., Industrial AI enabled prognostics for high-speed railway systems. In: 2018 IEEE International Conference on Prognostics and Health Management (ICPHM), Seattle, USA: IEEE, (2018) 1–8.
[15] C. Cheng, W. Wang, X. Meng, et al., Sigma-mixed unscented Kalman filter-based fault detection for traction systems in high-speed trains, Chin. J. Elec. 32 (5) (2023) 982–991.
[16] N. Qin, J. Du, Y. Zhang, et al., Fault diagnosis of multi-railway high-speed train bogies by improved federated learning, IEEE Trans. Veh. Tech. 72 (6) (2023) 7184–7194.
[17] W. Yu, D. Huang, L. Cai, et al., Event- triggered sliding-mode cruise control for multibody high-speed train, In: 2022 IEEE 11th Data Driven Control Learn. Syst. Conference (DDCLS) (2022) 537–542.
[18] Y. Zhang, N. Qin, D. Huang, et al., High-accuracy and adaptive fault diagnosis of high-speed train bogie using dense-squeeze network, IEEE Trans. Veh. Tech. 71 (3) (2022) 2501–2510.
[19] G. Xin, Z. Li, L. Jia, et al., Fault diagnosis of wheelset bearings in high-speed trains using logarithmic short-time fourier transform and modified self-calibrated residual network. IEEE Trans. Indust. Inf. 18 (10) (2022) 7285–7295.
[20] J. Ren, W. Jin, Y. Wu, A CNN-based structure for performance degradation estimation of high-speed train lateral damper. IEEE Access 8 (2020) 198139–198151.
[21] F. Peng, S. Kang, X. Li, et al., A heuristic approach to the railroad track maintenance scheduling problem, Comput. Aid. Civ. Infrastruct. Eng. 26 (2) (2011) 129–145.
[22] A.C. Nugraha, S.H. Supangkat, I.G.B. Nugraha, et al., Detection of railroad anomalies using machine learning approach, In: 2021 International Conference on ICT for Smart Society (ICISS), (2021) 1–6.
[23] R. Mohammadi, Q. He, A deep reinforcement learning approach for rail renewal and maintenance planning, Reliab. Eng. Syst. Saf. 225 (2022) 108615.
[24] S. Bressi, J. Santos, M. Losa, Optimization of maintenance strategies for railway track-bed considering probabilistic degradation models and different reliability levels, Reliab. Eng. Syst. Saf. 207 (2021) 107359.
[25] J. Xie, J. Huang, C. Zeng, et al., Systematic literature review on data-driven models for predictive maintenance of railway track: implications in geotechnical engineering. Geosciences 10 (11) (2020).

[26] Z. Pan, M. Chen, S. Lu, et al., Integrated timetable optimization for minimum total energy consumption of an ac railway system, IEEE Trans. Veh. Tech. 69 (4) (2020) 3641–3653.
[27] D.I. Fletcher, R.F. Harrison, S. Nallaperuma, Transenergy – a tool for energy storage optimization, peak power and energy consumption reduction in DC electric railway systems, J. Energy Storage 30 (2020) 101425.
[28] N. Qin, J. Du, Y. Zhang, et al., Fault diagnosis of multi-railway high-speed train bogies by improved federated learning, IEEE Trans. Veh. Tech. 72 (6) (2023) 7184–7194.
[29] S. Gao, Automatic detection and monitoring system of pantograph-catenary in China's high-speed railways. IEEE Trans. Instrum. Meas. 70 (2021) 1–12.
[30] R. Chen, Y. Lin, T. Jin. High-speed railway pantograph-catenary anomaly detection method based on depth vision neural network, IEEE Trans. Instrum. Meas. 71 (2022) 1–10.
[31] L. Chang, X. Pan, Z. Fu, et al., Robust online dynamic detection method for PAC operational status of high-speed trains basedonkey point positioning. IEEE Trans. Instrum. Meas. 71 (2022) 1–14.
[32] H. Hu, B. Tang, X. Gong, et al., Intelligent fault diagnosis of the high-speed train with big databasedon deep neural networks, IEEE Trans. Indust. Inf. 13 (4) (2017) 2106–2116.
[33] T. Li, Y. Xu, H. Tong, et al., Low-band information and historical data aided non-uniform millimeter wave beam selection algorithm in 5G-R high-speed railway communication scene. IEEE Trans. Veh. Tech. 71 (3) (2022) 2809–2823.
[34] J. Xu, B. Ai, T.Q.S. Quek, Toward interference suppression: ris-aided high-speed railway networks via deep rein-forcement learning, IEEE Trans. Wire. Commun. 22 (6) (2023) 4188–4201.
[35] W. Yu, D. Huang, Q. Wang, et al., Distributed event-triggered iterative learning control for multiple high-speed trains with switching topologies: a data-driven approach, IEEE Trans. Intel. Transp. Syst. 24 (10) (2023) 10818–10829.
[36] D. He, B. Ai, K. Guan, et al., Channel measurement, simulation, and analysis for high-speed railway communications in 5G millimeter-wave band. IEEE Trans. Intel. Transp. Syst. 19 (10) (2018) 3144–3158.
[37] X. Ren, W. Chen, M. Tao, Position-based compressed channel estimation and pilot design for high-mobility OFDM systems. IEEE Trans. Veh. Tech. 64 (5) (2015) 1918–1929.
[38] Y. Qiao, Y. Niu, X. Zhang, et al., Intelligent beam management based on deep reinforcement learning in high-speed railway scenarios, IEEE Trans. Veh. Tech. (2023) 1–15.
[39] T. Zhou, H. Zhang, B. Ai, et al., Weighted score fusion based LSTM model for high-speed railway propagation scenario identification, IEEE Trans. Intel. Transp. Syst. 23 (12) (2022) 23668–23679.
[40] J. Xie, S. Zhan, S.C. Wong, et al., A schedule-based model for passenger-oriented train planning with operating cost and capacity constraints. IEEE Trans. Intel. Transp. Syst. 23 (11) (2022) 21314–21328.
[41] X. Li, D. Li, X. Hu, et al., Optimizing train frequencies and train routing with simultaneous passenger assignment in high-speed railway network. Comput. Indust. Eng. 148 (2020) 106650.
[42] D. Chen, S. Ni, C. Xu, et al., High-speed train stop-schedule optimization based on passenger travel convenience, Math. Prob. Eng. 1 (2016) 1–10.
[43] J. Liu, H. Zhao, X. Dai, An improved adaptive particle swarm optimization method for high-speed train scheduling in unexpected events, In: 2022 IEEE 17th Int. Conf. Control Autom. (ICCA) (2022) 130–134.
[44] K. Wen, G. Zhao, B. He, et al., A decomposition-based forecasting method with transfer learning for railway short-term passenger flow in holidays. Expert Syst. Appl. 189 (2022) 116102.
[45] S. Zhao, X. Mi, A novel hybrid model for short-term high-speed railway passenger demand forecasting, IEEE Access 7 (2019) 175681–175692.
[46] Z. Zhang, C. Wang, Y. Gao, et al., Passenger flow forecast of rail station based on multi-source data and long short term memory network, IEEE Access 8 (2020) 28475–28483.
[47] Y. Tan, Y. Li, R. Wang, et al., Improving synchronization in high-speed railway and air intermodality: integrated train timetable rescheduling and passenger flow forecasting, IEEE Trans. Intel. Transp. Syst. 23 (3) (2022) 2651–2667.
[48] H. Su, S. Peng, S. Mo, et al., Neural network-based hybrid forecasting models for time-varying passenger flow of intercity high-speed railways, Mathematics 10 (23) (2022).
[49] L. De Donato, R. Dirnfeld, A. Somma, et al., Towards AI-assisted twins for smart railways: preliminary guideline and reference architecture, J. Relia. Intel. Environ. (2023) 1–15.
[50] P. Li, Y. Liu, S. Shao, System architecture and basic platform for intelligent high-speed railway, Railw. Sci. 2 (2) (2023) 257–272.
[51] M. Zhang, Q. Zhang, Y. Lv, et al., An AI based high-speed railway automatic train operation system analysis and design. In: 2018 International Conference on Intelligent Rail Transportation (ICIRT), Singapore: IEEE, (2018) 1–5.
[52] X. Xiao, Y. Wang, L. Jia, et al., Research on integrated monitoring and early-warning platform for safe high-speed railway operation. In: 4th International Conference on Digital Image Processing (ICDIP), Singapore, (2012).
[53] P. Li, Y. Niu, H. Wu, et al., RIS-assisted scheduling for high-speed railway secure communications, IEEE Trans. Veh. Tech. 72 (3) (2023) 3488–3501.
[54] Y. Wang, W. Zhang, X. Wang, et al., Improving the security of LTE-R for high-speed railway: from the access authentication view, IEEE Trans. Intel. Transp. Syst. 23 (2) (2022) 1332–1346.