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Review

REVIEW

A review on artificial intelligence in high-speed rail

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Abstract

High-speed rail (HSR) has brought a number of social and economic benefits, such as shorter trip times for journeys of between one and five hours; safety, security, comfort and on-time commuting for passengers; energy saving and environmental protection; job creation; and encouraging sustainable use of renewable energy and land. The recent development in HSR has seen the pervasive applications of artificial intelligence (AI). This paper first briefly reviews the related disciplines in HSR where AI may play an important role, such as civil engineering, mechanical engineering, electrical engineering and signalling and control. Then, an overview of current AI techniques is presented in the context of smart planning, intelligent control and intelligent maintenance of HSR systems. Finally, a framework of future HSR systems where AI is expected to play a key role is provided.

Keywords: high-speed rail; artificial intelligence; smart planning; intelligent control; intelligent maintenance

1. Introduction

Artificial intelligence (AI) refers to agents or systems that are capable of learning in similar ways to human cognitive processes and that autonomously reason and solve problems by imitating biological processes. With the rapid development of new technologies and breakthroughs in computation power and cloud computing, nowadays AI not only has the capacity to adapt to changing environments, but can also improve its own performance over time. There are plenty of successful AI applications which have proven effectiveness. For example, researchers found that AI-based automated analysis of chest CT images can help radiologists save time on diagnosis and consequently create a $3 billion economic saving per year [1]. In the transportation sector, especially in HSR systems, AI can make a huge contribution to addressing growing concerns about ride comfort, system safety and stability and rail expansion-related energy consumption.

The first commercial HSR line, also known as Tokaido Shinkansen, was launched by Japanese

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National Railways in 1964 between Tokyo and Osaka at a running speed of 210 km/h. The technical innovation quickly attracted substantial attention worldwide for its convenience, high capacity, reliability, safety and sustainability in competition with the aviation and automotive sectors. Several European countries, particularly France, Italy, Spain and Germany, one after another expanded and proliferated their HSR network services. Meanwhile, the world commercial speed record has been constantly broken in the following decades. It is notable that China has scaled up the development of HSR in both new high-speed line distance and trainset numbers enormously in the past decade. Up to February 2020, there are 52 484 km high-speed lines in operation with speeds above 250 km/h around the world, and China alone accounts for 67.4% with 35 388 km in total [2]. Although there is no universal definition of HSR, standards have become unified around the world in recent years. The European Union (EU) Directive 96/48 [3] defines the speed as over 250 km/h for dedicated new lines and over 200 km/h for upgraded lines in respect of the infrastructure capabilities.

The development of HSR relies on technological advancement. The emergency of new technologies such as AI has brought new opportunities as well as challenges for the development of HSR. This paper presents a comprehensive review of the state-of-the-art development of HSR, and in particular the approaches to increase the performance of design, operation and maintenance by utilizing AI techniques. The remainder of the paper is organized as follows. Section 2 gives a preliminary discussion on the safety, reliability, availability and cost of key subsystems in HSR. Section 3 presents a summary of different AI techniques and their applications in HSR, and then future requirements and opportunities are discussed in section 4. Finally, conclusions and challenges for further study are presented in Section 5.

2. A brief introduction to the high-speed rail system

The HSR system is an integration of a large number of subsystems and techniques from different subject areas. A new HSR line often consists of specialized rolling stocks and dedicated tracks. The construction cost increases proportionally with the design speed. According to [4], the average cost of 11 European lines (with no tunnelling projects) stands at €25 million per km. The staggering costs of building infrastructure for high-speed (above 300 km/h) operation require careful system design and high-quality arrangements.

2.1 Civil engineering related factors

The track system is a critical part of HSR, and corrections are very difficult to make after construction. Daily maintenance is also costly and is mainly arranged based on the construction design. For wheel/rail technology, rails are designed to withstand enormous load when trains pass through. Traditional track structure consists of rails, fasteners, sleepers, ballast and underlying subgrade. The sleepers, laid perpendicular to the rails, can separate the pressure evenly to the track ballast and subgrade and fix track gauge. The track technologies vary from country to country. The French rail network adopts traditional ballasted track for HSR, whereas in other European countries and parts of the world ballastless tracks (slab tracks) are preferred because of the reduced weight, low demand for maintenance, long service life and no damage from flying ballasts to running HSR [5]. In [6], Zhai et al. show that the requirements of stiffness and settlement for HSR tracks are strict to ensure track regularity. Track safety would be severely affected by track stress and vibration.

Due to ecological requirements, such as the protection of historical culture areas and arable land, tunnels and bridges (elevated structures) are widely considered in HSR designs, most notably in China. The average bridge proportion of total track length is greater than 50% [7], while more than 10 000 tunnels with a length of over 8000 km had been constructed by 2013 [8]. The force between continuous welded rails (CWRs) and the ballastless-deck bridge is greater than the subgrade, and the influence is magnified for long-span continuous bridges [9]. Therefore, the analysis and simulation of the static and dynamic behaviour of ballastless tracks under various loadings and locations are of great significance in design. Both short- and long-term behaviours, during the whole life time, equally dominate train operation conditions.

An early study by Krylov [10] theoretically investigated the effects of ground vibrations induced by HSR moving at speeds approaching or exceeding the velocity of Rayleigh waves. The results show a rise of 70 dB in averaged ground vibration level for a train's moving speed from 50 km/h to

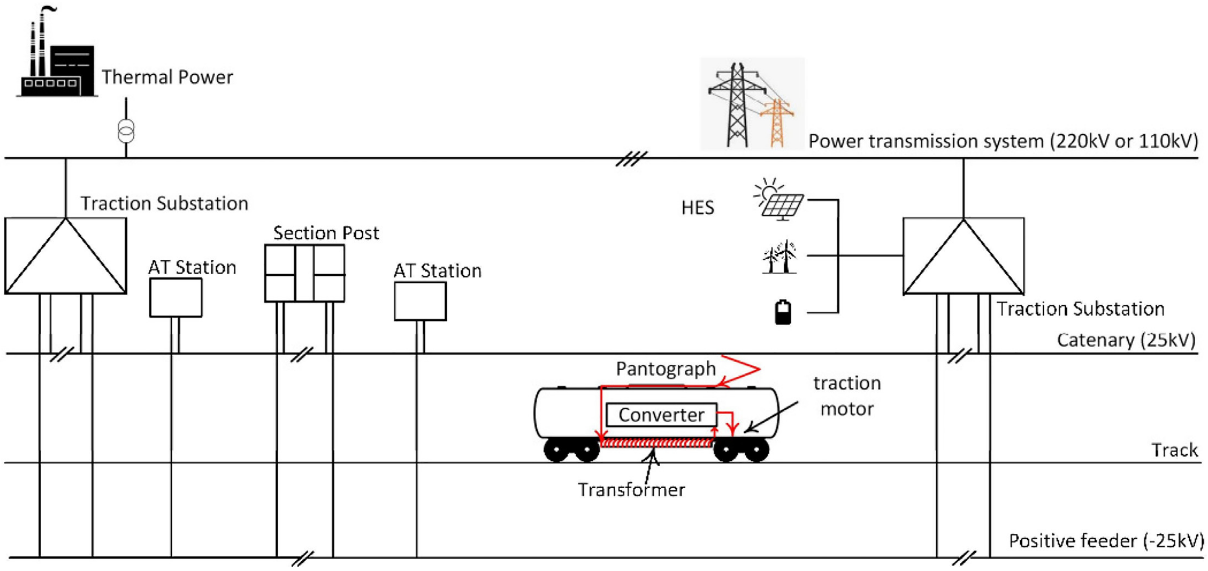

Fig. 1. Simplified diagram of an AC traction system for HSR

500 km/h. Krylov recommended avoiding soft soil with low Rayleigh wave velocity (around 100 m/s or 360 km/h) in the design phase, or taking steps to mitigate the 'noise'. Madshus and Kaynia [11] analysed the vertical vibration displacement signal data collected by a series of electronic sensors, accelerometers and seismometers at the top of the embankment and in the ground in Sweden. The propagation and attenuation characteristics of the vibration in the soft soil foundation are further investigated in [12]. Unfortunately, very limited information has been reported in the literature about the severity of the problem.

2.2 Mechanical engineering related factors

In a train, the bogie is an essential equipment which steers the car and provides traction and braking forces. It is joined to the chassis of the bodyshell, with axles and wheels attached. The bogie enables trains to turn in a curve by reasonable design and also guarantees passenger comfort and operational safety. To achieve this, two suspension systems play an important role. The primary suspension system acts like the tyre on an automobile. It is placed between the wheel axles and the bogie. The secondary suspension system links the bogie to the bodyshell. Thanks to the suspension system, track irregularities are absorbed and cut off, leading to a controllable lateral movement of the car. There are two types of bogies, motorized ones dedicated to the traction and load-bearing ones for braking and on-track steering.

One of the main techniques for monitoring the running status of the train is to collect and analyse the vibration signals by mounting sensors on the train bogies. Mechanical vibration analysis based on monitoring data of bogies has become a hot research topic [13]. According to Hu et al. [14], the health monitoring of bogies is entering into the 'big data' era. Traditional signal processing-based and diagnostic experience-based methods, including empirical mode decomposition and wavelet analysis, cannot meet the requirements of the rapid development of HSR and maintenance work when massive vibration data are collected. Therefore, a highly efficient and accurate method is an urgent research need, especially a deep understanding of signals with the coupling of fault information.

2.3 Electrical engineering-related factors

A simplified alternating current (AC) traction system is illustrated in Fig. 1, including power transmission system, catenary (also known as overhead contact line) and positive feeder line. The traction power supply system introduces external power supply. In the context of energy conservation and environmental protection, the integration of renewable energy sources and energy storage units in the railway power systems has attracted substantial interest worldwide. In [15], Pankovits et al. propose a hybrid energy system composed of PV panels, wind turbines, foreseeable sources and storage units for a railway substation, with minor changes to its natural structure. In addition, considerable regenerative braking power lays out the possibility of energy recovery by advanced power electronics, since the traction motor functions as a generator in braking mode. Aguado et al. [16] take into account regenerative braking capabilities and analyse the renewable energy impact on a real Spanish HSR case study. The results show that the new configuration provides a significant improvement on cost and energy savings, with 33.22% and 9.63% respectively. Liu et al. [17] analyse the optimal sizing and daily scheduling of energy storage units, which largely reduces the electricity bill.

There are several feeding modes in the traction power supply system (TPSS), comprising boosting transformer (BT) feeding system and autotransformer (AT) feeding system and track return feeding system. Compared with other feeding systems, the AT system has both technical and economic advantages. It can decrease the voltage drop along the catenary, which results in increased voltage level and reduced power loss [18]. The distance between two transformers is longer than in the case of BT, so the number of substations is lower at the same distance. However, the most typical and severe power quality problems in HSR are unbalance, reactive power and harmonic resonance [19] because the loads on two power supply arms are seldom balanced. Various technologies for solving these problems have been investigated in recent years. The cophase traction power system can avoid the power quality problems caused by the split sections in the traditional system [20]. For such a system equipped with an active power balance conditioner (APC), only single-phase current feeds to the catenary.

The simulation and monitoring of traction power supply systems are very important for fault prediction and fault location analysis in HSR. The proliferation of converter-based electrified systems has resulted in significant voltage and current distortions in both the traction power supply system and the utility system. The dynamic nature of HSR makes the assessment of power-quality (PQ) problems quite difficult, and there is an urgent need for techniques that can quantify the PQ impacts for TPSS planning and design [21].

2.4 Signalling and control-related factors

Conventional trains rely on manned control and trackside singling and surveillance devices. But at high speed it is unrealistic for train drivers to see the signals. In order to undertake safe driving of the Shinkansen, an automatic train control (ATC) system was built and tested in 1964. The system replaces the trackside signalling with cab signalling, providing an auxiliary system of smooth deceleration patterns that can help energy saving and brake wearing. The big revolution of train control systems, from trackcircuit-based train control to communication-based train control, permits safe movement of trains during operation under different loading, track and weather conditions [22].

Generally, the ATC system includes Automatic Train Protection (ATP), Automatic Train Operation (ATO) and Automatic Train Supervision (ATS) subsystems [23]. The train's onboard equipment stores the track database including curvature, gradient and station information, and calculates the distance-to-go speed profile for the train by utilizing the real-time location of the train, the permitted speed and environmental data. Most of the researches on driving regimes are based on optimal control theory [24]. This segments the speed profile into four modes: maximum acceleration, cruising, coasting and maximum braking. The system is requested to find the optimal sequence of the driving modes which meet the time and safety requirements and recent energy efficiency requirements.

The European Train Control System (ETCS) is part of the European Rail Traffic Management System (ERTMS). After more than 10 years' effort from 1996, it brings in interoperability and technical standards of train control systems of cross-border HSR in Europe [25]. The similar concept of CTCS (Chinese Train Control System) was proposed in 2002 in China. If a train is equipped with CTCS appliance and functionality, it can operate on any CTCS line without technical restrictions. The system consists of an onboard subsystem and a trackside subsystem. A CTCS level-3 system is illustrated in Fig. 2. The onboard equipment includes Driver-Machine Interface (MMI), Vital Computer (VC), GSM-R Radio Transmission Unit (RTU), Speed and Distance processing Unit (SDU), Balise Transmission Module (BTM) and Track Circuit Receiver (TCR). The trackside outdoor equipment includes ZPW-2000 track circuit, balise and GSM-R radio Base Station (BTS). The trackside indoor equipment includes Radio Block Center (RBC), Train Control Center (TCC), Temporary Speed Restriction Server (TSRS), Computer-Based Interlocking (CBI), GSM-R Mobile Exchange Center and Centralized Traffic Control (CTC).

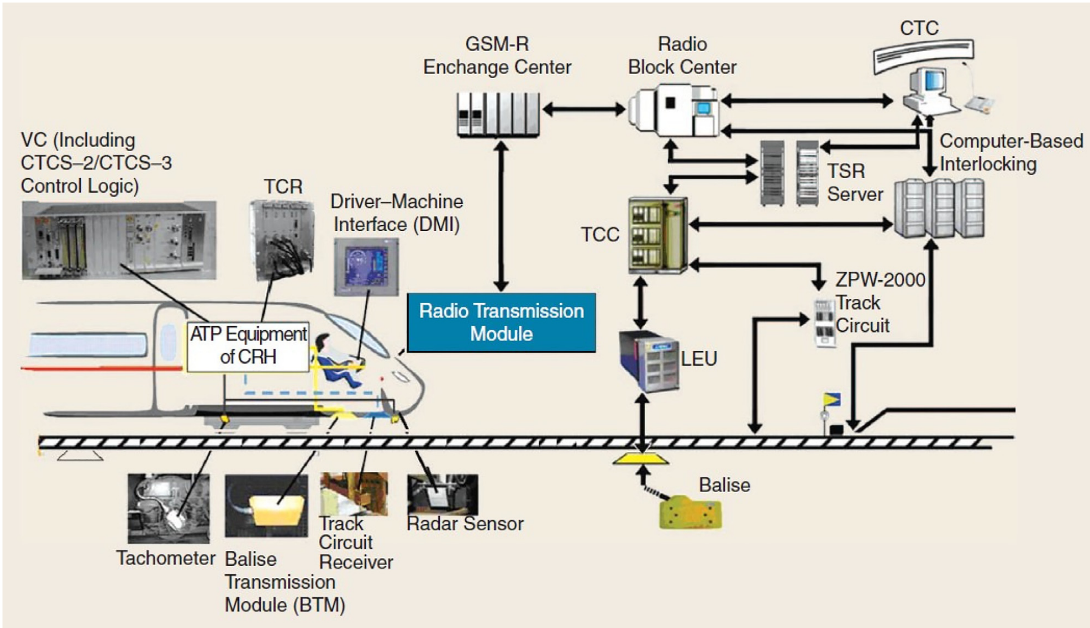

Fig. 2. A CTCS level-3 system for HSR [26]

2.5 Transportation engineering-related factors

Compared with the requirements of conventional train lines, train timetabling problems (TPPs) for HSR become very challenging for the Railway Dispatching Department, as the train frequency dramatically increases due to the high speed and passenger demand [27]. It is observed that the passenger traffic figure almost tripled between 2010 and 2018, increasing from 245.1 billion passengers per km to 956.1 billion passengers per km [28]. Therefore, the objective of a train time is to provide a feasible service time for passengers to plan their journey and meanwhile to maintain low energy consumption over the corridor. It must take into account the actual infrastructure utilization ratio (such as tracks and rolling stocks) and accommodate the fluctuation of passenger volumes over time. Also, the trajectory and operation speed of HSR have close ties to the train operation.

A basic train timetable example consisting of multiple trains among five stations within two hours is illustrated in Fig. 3. The physical model is then expressed as a graph $G = (V, E)$ in Fig. 3(a), comprising a set V of stations together with a set E of train line sections. For each section, the running time is a summation of the minimum running time over the corridor and the dwelling time. It can be seen from Fig. 3(b) that some train lines increase the dwelling time at stations, while some others skip a few stops.

To solve the problem, some restricted conditions are imposed, such as constraints on minimum headway, station capacity, maintenance window and minimum dwell time. For such a complex and busy system, there is no tolerance of signal delays or command errors. Even a short delay on a single train may cause a large-scale system collapse due to the strict punctuality requirement. As a result, there is an urgent need for a reliable control and signalling system which can balance efficiency and potential unforeseen circumstances.

3. AI techniques for HSR systems

As a sub-field of computer intelligence, the real potential of AI techniques has not been fully realized due to the late 1990s vigorous growth of computational power following Moore's law. The powerful learning capabilities have led to an unprecedented tie of AI with many other fields such as economics, statistics and mathematics [29]. In this section, AI-related methods that have been successfully employed in HSR systems will be reviewed.

3.1 Smart planning

Smart planning, also refering to automated planning and scheduling, is a branch of AI focusing on the strategies or action sequences for designed goals in a multidimensional space [30]. Models and policies are adaptive according to the environment and usually solutions are acquired by

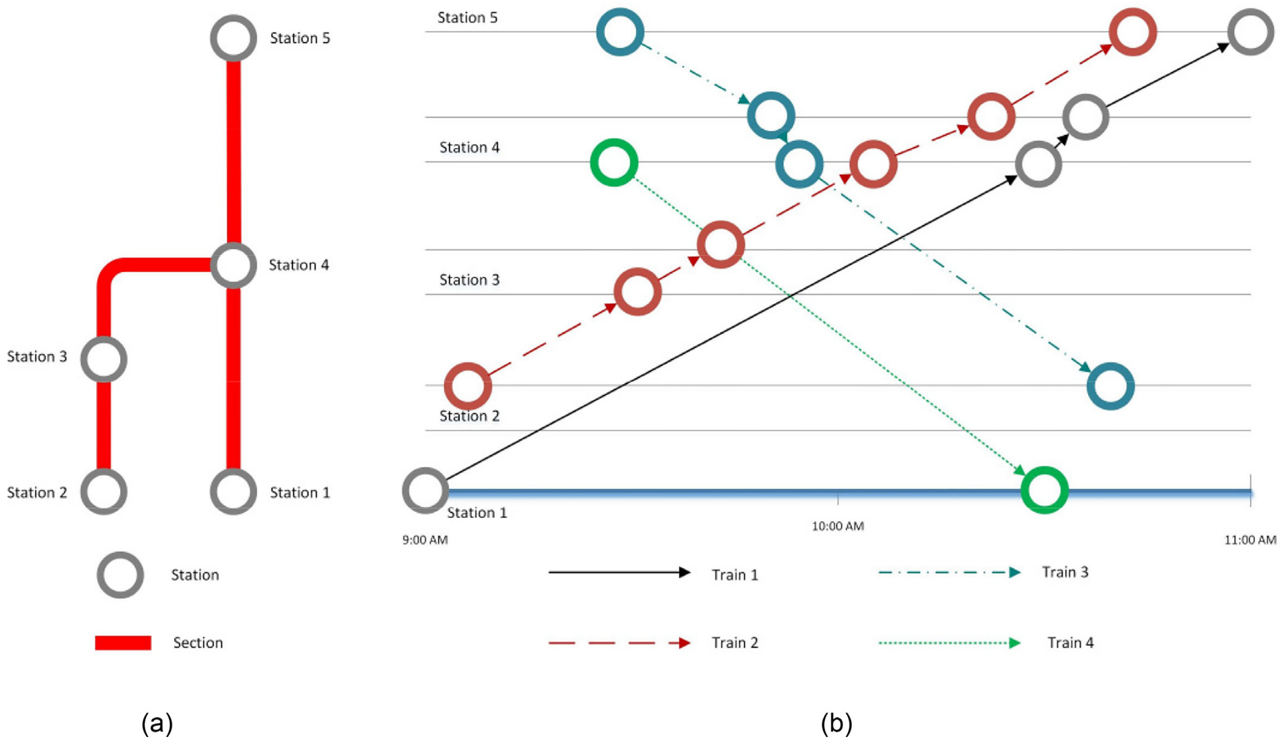

Fig. 3. A basic timetable for HSR. (a) The physical model; (b) The running time.

resorting to iterative processes of trial and error. Dynamic programming, reinforcement learning and local search algorithms and heuristic optimization are involved.

Researches about planning in HSR have covered a wide range of topics, such as train timetable planning (see section 2.5), rolling stock planning and crew scheduling planning for train operation companies. They also include reliable digital rail solutions that help operators improve performance and provide a better customer experience.

3.1.1 Timetable synchronization and optimization. Passenger demand is the fundamental issue [31]. An efficient planning should consider operation effectiveness such as safety, ride comfort and convenience, which always refers to trip time from the passengers' viewpoint [32]. Ghoseiri et al. [33] introduced the total passenger time as the passenger satisfaction criterion.

In [34], the research is focused on minimizing the total passenger waiting time at stations. The train stop pattern is given. Further, Jiang et al. [35] employed a heuristic solution to examine the maximum train frequency and suitable stopping plans that have minimal impact on original timetables for a congested Chinese high-speed JingHu line containing 387 trains in a given time interval. The model used explicitly takes into account the deceleration and acceleration times at stations, as well as the overtaking constraints. The results show that with effective stopping plans, additional trains can be scheduled with minor changes of existing ones.

Regarding the railway company, cost has long been the top factor under consideration. Yue et al. [36] used a train trajectory's profit model to optimize the TPP, including stopping times and number of stops. An iterative process based on the column generation-based algorithm improves the profit by 30% and line capacity by 27% in the case study of the Beijing-Shanghai corridor. To maintain competitiveness against other transportation modes, Cadarso et al. [37] developed an integrated scheduling model associating to frequency planning, timetable, rolling stock schedule and passenger demand. For the sake of robustness, Sels et al. [38] introduced a fast and robust timetable generating method which was proven on the Belgian railway network with 196 hourly passenger trains. The aforementioned off-line train timetable generating methods are designed to solve the problem within two hours. In [39], an online rescheduling following a small perturbation is proposed. The aim is to find the minimal total accumulated delay by adjusting departure and arrival times for each train and station resources based on a permutation-based evolutionary algorithm.

More comprehensive insights can be found in [40, 41].

Another important issue related to the HSR is energy consumption [24], which has drawn substantial interest in recent years on the planning of renewable energy integrated with hybrid energy storage devices. Pankovits et al. [15] propose a generic architecture of hybrid railway power substation and evaluate the optimal planning of energy sources and storage units for a day based on an iterative optimization process. Another study focusing on the optimal sizing of energy storage systems is carried out in [17]. The authors adopt a heuristic algorithm, namely grey wolf optimization with CPLEX solver for a mixed integer linear programming model. A real case study for a Spanish HSR supplied with renewable energies with regenerative braking capabilities is analysed in [16]. An improvement in cost savings of 33.22% and energy savings of 9.63% has been achieved.

3.1.2 Knowledge-based customer service. Insufficient information of delayed or cancelled trains and slow responses at railway terminals can make the journey a daunting experience for customers. The frontline staff of train companies are in need of instant access to a reference library and service information to improve customer service. An expert system is a good solution to solve such complex problems by reasoning through a knowledge base. This system can perform as a decision-making tool like a human expert.

A typical sales operator of a railway network issues pricing periodically. Meanwhile, the passenger capacity allocation of HSR is decided based on internal conditions, such as remaining seats and time to departure, as well as external conditions such as seasonal factors and weather conditions. Recently, Kamandanipour et al. [42] borrowed the idea of revenue management from air transportation to develop an expert system to maximize the profit of an independent operator by integrating dynamic pricing and capacity management. Their model also provides a choice of multiple service classes that will change the demand over a planning horizon. Due to the complexity of the problem, an efficient metaheuristic algorithm is used to solve the data-driven non-convex optimization problem and a simulation-based algorithm is applied to calculate the fitness. In [43], an analytical two-stage model is proposed for the dynamic pricing and seat allocation problem with additional consideration of multiple origin-destination pairs. The results of the case study of the Beijing-Shanghai HSR line in China show that the final revenue can be increased from 4.47% to 4.95% by using the dynamic pricing mechanism. In addition, demand increases for short-haul journeys and decreases for long-haul journeys.

Although the aforementioned model provides useful insights for HSR to enhance service quality, some important features in HSR services and management are still ignored, such as different groups of passengers and ticket booking preferences. By leveraging machine learning methods, the prediction of customers' train choice can be enhanced and evolve with time [44]. It is therefore of great potential to integrate them in revenue management tools for HSR.

3.2 Intelligent control

Intelligent control achieves automation using various AI computing approaches like fuzzy logic, artificial neural network (ANN) and genetic algorithm (GA) [45]. Fuzzy control, in contrast to classical discrete logic, introduces fuzzy logic which is used to represent continuous values between 0 and 1. It is a good interpretation of manual operations. In many cases where a mathematical model does not exist, a system based on empirical rules is more effective. ANN is a framework to implement different machine learning algorithms and has the ability to process complex data inputs. It mimics the behaviour of biological neurons. The learning paradigms can be categorized into three types: supervised learning, unsupervised learning and reinforcement learning. ANNs have the ability to learn and model non-linear and complex relations. Also there are many variants, such as convolution neural networks, long short-term memory, deep belief networks and compond hierarchical-deep models, etc. The combination of fuzzy logic and ANN leads to the development of neural fuzzy systems. Genetic algorithms are metaheuristic-inspired methods that are commonly used to generate high-quality solutions to optimization and search problems. They belong to evolutionary algorithms that can effectively find the optimal or quasi-optimal solution through an iterative mechanism within limited time.

3.2.1 Speed control and trajectory control. The researches related to speed and trajectory control of HSR are an active field, and usually the proposed methods are hybrid for specific conditions. In 1998, Hwang [46] proposed a fuzzy control model to optimize the trajectory of a single train by compromising trip time and energy consumption. Sun et al. [47] developed a genetic algorithm-based train control method for a multi-objective optimization model of the train routing problem. The model takes into account average travel time, energy consumption and user satisfaction. Similarly, particle swam algorithm is used in a simulation system of HSR to optimize the energy consumption problem [48]. Three commonly adopted searching algorithms—GA, ant colony optimization (ACO) and dynamic programming—are comparatively studied in a distance-based train trajectory model [49]. As a result, the authors recommend the adoption of more than one method. Unlike the aforementioned models, Cucala et al. [50] define the uncertainty in delays as fuzzy numbers and use a GA-based ecodriving design for a real Spanish HSR. In comparison with current commercial data, a significant energy saving of 6.7% is achieved. In [51], an adaptive iterative learning control strategy for HSR is proposed, while Song et al. [52] developed a dual optimization speed curve method. A guidance speed curve is searched by offline global optimization before the train moves. The reference speed curve is optimized in real time by online local optimization, where predictive control and slope analysis are combined for the actual operation. Further, a T-S fuzzy bilinear model is proposed in [53] based on the nonlinear dynamics of the train, and an adaptive predictive control approach is then used for online adjustment of the model's parameters.

An astonishing breakthough is the application of intelligent control in the ATO system (see also in section 2.4). On 30 December 2019, a new Chinese high-speed train (also known as the Beijing-Zhangjiakou railway line) was operated at speeds of up to 350 kph, and is widely recognized as the world's first driverless train [54]. The train can automatically depart, operate between stations and adjust its operation status to meet the precise timetable without human drivers. However, the increasing frequency and intensity of extreme weather events will bring new challenges to the operation and control of HSR [55]. Further research is needed to evaluate the impacts of weather conditions on the train operation and punctuality of the HSR system under different probabilities of unexpected events.

3.2.2 Intelligent equipment. The intelligent control system of HSR can monitor and predict abnormal conditions and automatically switch to different driving modes. All of these new features rely on new technologies and designs such as cloud computing, big data and the Internet of Things. Dong et al. [56] proposed a novel and practical vehicular cloud computing (VCC) for HSR. After taking into account the key obstacles of frequent handover at high speed, large volumes of data and complex degrees of importance situations, a three-layer architecture of secure VCC system to improve the safety and efficiency is proposed. The real-life experiments in China show that the proposed system outperforms its counterparts in respect of authentication, data encryption and transmission efficiency. Gong et al. [57] developed a novel cyber fusion system that can deal with heterogeneous multi-source train location data. A collision avoidance warning system is proposed in [58]. The system is based on a Linux-based hardware and Internet of Things-based signalling system to improve the predictability of collision occurrence. In [59], several representative railway communication scenarios are reviewed, including train-to-infrastructure communications, inter-car communications, intra-car communications, communications inside the station, infrastructure-to-infrastructure communications and wireless sensor networks. The analyses raised new requirements for the Internet of Things and smart trains, such as standardization, interoperability, scalability, energy efficiency and cyber security. A more secure paradigm requires redundancies and alternative control methods. For example, in case of failure, the system needs to switch to the redundant equipment without disturbing the safety control of the train through the signalling system.

3.3 Intelligent maintenance

Intelligent maintenance, or e-maintenance, addresses the fundamental needs of monitoring degradation through collected data of machinery. It utilizes predictive intelligence tools to detect faults rather than the traditional 'fail and fix' maintenance mechanism [60]. With evolving technologies of tether-free communication, the behavior of a complex system can be analysed by means of advanced sensors, data collection, data storage/transfer and data analytic tools developed for a specific purpose. More hidden information from the historical data can be extracted through intelligent prognostics that continuously track health conditions and extrapolate risks. A cyber-physical-based maintenance system enables applications of AI technologies for Prognostic and Health Management (PHM) [61]. It includes fault prediction, risk assessment, health evaluation and reliability analysis [62]. By taking advantage of real-time data streams, advanced algorithms and data analytics perform as a knowledge-based expert system which aims at an optimal decision of the system. There are four major types of maintenance modes, namely breakdown maintenance (BM), preventive maintenance (PM), hazard detection (HD) and condition based maintenance (CBM) [63]. In [64], a high-level preventive maintenance planning method is proposed for HSR. A simulated annealing-based optimization algorithm is developed to decide whether a train needs maintenance or not.

3.3.1 Data mining. An important feature of the HSR system is that the data used to analyse is multi-source and heterogeneous, as a variety of different assets are incorporated such as on-board equipment, traction supply system and tracks. Feature extraction is one of the key steps in data mining for HSR. However, a lot of problems appear in practical applications. For example, traditional signal processing methods are restricted by the number of samples. Hence, big data technologies are suitable to data mining and analysis of HSR [65].

Xie et al. studied the vibration signal spectrum through a set of data of locomotive shock absorbers preprocessed by FFT [66]. The result shows that a four-layer Deep Belief Network (DBN) performs well in terms of both accuracy and stability for a data set of 14 000 cases. Unlike the shallow architecture models, DBN has many advantages. It can realize nonlinear approximation of complex dynamics and avoid over-fitting problems. However, the DBN model is vulnerable to the change of the number of network layers and the size of hidden units, and the performance is not stable. In [67], Guo et al. combine the DBN with classification ensemble technologies (including SVM, KNN and RBF) in a hierarchical way. By taking advantage of self-learning deep neural networks, Hu et al. [14] developed an accurate recognition method for six fault scenarios of bogies using big data analytics. Intelligent diagnosis is realized as the fault features are self-adaptive and no signal processing technologies and engineering experience are needed. The accuracy of the proposed method is the highest compared with multihidden layer BPNN, single-hidden layer BPNN and GA-BPNN. In addition, the feature extraction capabilities of the previous algorithms are also analysed based on the clustering method and the scatter diagram shows the superiority of deep neural networks. [32] presents a joint neural network CRNN that integrates 1D-CNN (convolutional neural network) and SRN (Simple Recurrent Unit). The 1D-CNN part of the presented CRNN extracts the depth characteristics of the bogie signals. The stacked SRU section learns the sequence information of the signal frame in each layer of the forward delivery. Therefore, the proposed method can quickly identify bogie sequence information to ensure the real-time and accuracy requirements of diagnosis.

The current strategy of TPSS maintenance is passive maintenance, relying on preventive maintenance, fault repair and artificial inspection [68]. It brings an inefficient repair problem which is costly and imposes a heavy workload. Although many sensors are employed in TPSS, the performance of existing approaches is limited due to the available real-time data collected from the monitoring system. A vast number of historic data are under-utilized, which demands the development of more advanced maintenance analysis tools. For example, a data-driven incipient fault estimate of inverters in HSR [69] is proposed to detect minor abnormalities and it can be extended to other electrical systems through nonlinear projections.

3.3.2 Computer vision. Computer vision is capable of acquiring, processing, analysing and understanding digital images. When it acts as a vision sensor, high-level information will be transmitted to AI system for further interpretation. As a non-contact detection method, computer vision-based robotics can replace the manual detection with asset detection. The benefits of significant cost reductions on investigation and operation have gained much attention from railway operation departments. Several applications of computer vision can be found in track [70, 71], bridge [72], pantograph [18, 73] and catenary maintenance [74]. An automatic visual inspection of fasteners of track is presented in [70]. The authors use fastener samples to train a generative and data-driven probabilistic model. The proposed model achieves

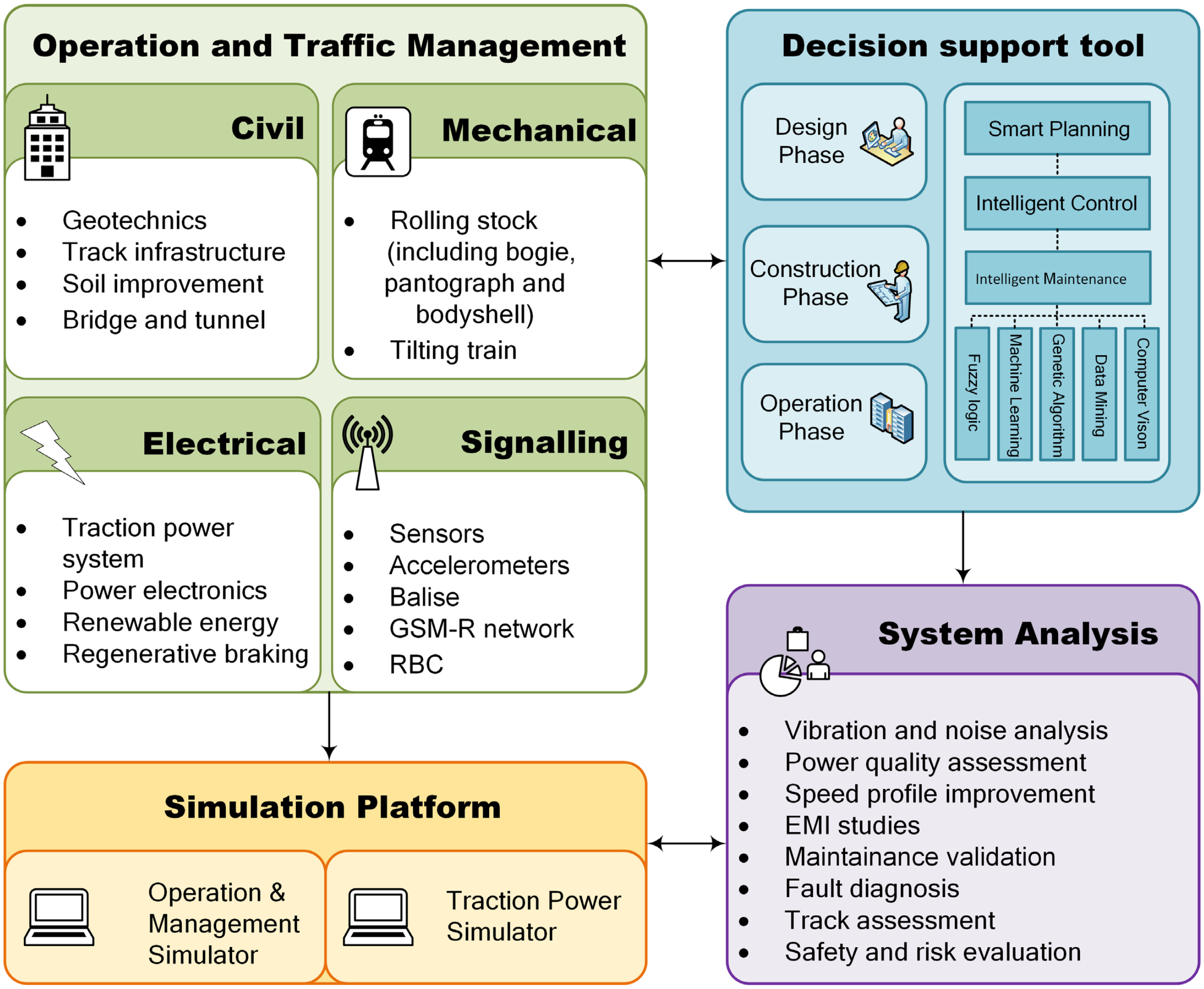

Fig. 4. A systematic framework for future HSR system

the highest accuracy, compared with conventional classifiers, i.e. boosted tree, latent SVM and neural networks. In [72], a probabilistic model is constructed in order to predict the vertical deflection of a railway bridge. The bridge data are acquired from two HDTV video cameras which are installed at the end of the bridge. Han et al. [74] present a deformable part model (DPM) algorithm for the catenary system. The method can quickly extract the target image instead of scanning the entire image. In [73], Canny edge detection and Hough transform algorithms are used to determine the height of a pantograph system. Experimental results show that the proposed method works efficiently in real time. Zhu et al. [75] study the abrasion condition of a pantograph slipper based on Canny edge detection. Instead of artificial inspection, computer vision techniques considerably improve the accuracy and reliability of asset management.

4. Requirements and architecture of future HSR

HSR construction is always a critical national project. To date, over 20 countries have had high-speed lines in operation worldwide [2]. More cross-border railways such as the corridor from Turin to Lyons are being planned, shortening the commute time between cities, regions and countries. However, various standards and system incompatibilities hinder the development of HSR. Fig. 4 illustrates a designed framework for a future HSR system that satisfies the requirements of customer comfort and operation efficiency.

Based on the AI methodologies described before, the architecture is supposed to achieve:

(i) An online analytic tool to support system operation and management. Four parallel function modules are required: rolling stock modelling, Driver Advisory System (DAS), fault prediction and emergency timetable rescheduler. Since each computation module requires a huge amount of input data and generates many raw outputs, a common data format may be generated for cross-platform applications. With the further development of technology, driverless module will replace DAS.

(ii) A user-friendly traction power analytic tool. The package is run by an integrated platform that obtains input data from TPSS, and during operation time the simulation is run in order to ensure the steady and high efficient operation of the supply system. An advanced database management technique should be developed to support the smooth running.

(iii) A decision support tool system running through the design phase, construction phase and operation phase. In previous analysis, AI-related techniques show great performance on the operation phase. But the applications in the design and construction stages are limited. One reason for the problem is the loose connection between civil engineering and AI. In fact, AI-aided analysis such as soil-structure interaction and terrain layout can reshape the customary procedures, in particular with the further maturity of 5G communication and big data technologies.

In recent years, some attempts have been made to use AI to analyse HSR dynamics. Hitachi [76] collected 13 daily basis operation data of UK's High Speed 1 project, such as rolling stock operation information and track infrastructure information, and used them to estimate the effect of energy consumption under different traction modes. Some startups like D-Rail are introducing new technologies into infrastructure monitoring, operation trend analyses and automated alarms with cutting-edge AI solutions [77]. It is projected that AI will continue to play a crucial role in supporting decision and analysis for new locomotives and TPSS. As parts of smart city initiatives, the design of intelligent HSR is required to be coincided with the development of railway stations and other transportation means to improve the efficiency of energy consumption, on-board security and labour saving.

5. Conclusions

This paper has presented a comprehensive survey of cross-disciplinary researches on the application of AI techniques in the HSR system, as well as an insight into the future direction of the integrated platform and analysis tools. The main AI techniques discussed include, but are not confined to, fuzzy logic, machine learning, genetic algorithms, data mining and computer vision, which are used for: (1) smart planning, (2) intelligent control and (3) intelligent maintenance.

But many challenges need to be considered before the full potential of the AI techniques can be achieved in HSR. First, the robustness of algorithms should be carefully verified. As there are many 'black box' models which lack interpretation of the inner dynamics, it will trigger cascading failures even if a small error appears in the design phase. Second, from the eco-tech aspect, the deployment of new AI-based instruments and devices for the railway system is still costly, and it will also consume a lot of the resources for staff training. It is not in the railway operation companies' interest in the short term. Third, the security and stability of the AI system can be confronted with various new challenges. Cryptographic techniques and other new methods are needed to tackle these various challenges relating to security.

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References

1. *Harvard Business Review.* 10 promising AI applications in health care. https://hbr.org/2018/05/10-promising-ai-applications-in-health-care. 2018. (13 December 2018, date last accessed).
2. UIC Passenger Department. High speed lines in the world. https://uic.org/IMG/pdf/20200227_high_speed_lines_in_the_world.pdf. 2020. (10 June 2020, date last accessed).
3. European Commission. September. Council directive 96/48/ec of 23 July 1996 on the interoperability of the transeuropean high-speed rail system. https://www.eca.europa.eu/en/Pages/DocItem.aspx?did = 46398. Official Journal.
4. European Court of Auditors. A European high-speed rail network: Not a reality but an ineffective patchwork. https://www.eca.europa.eu/en/Pages/DocItem.aspx?did = 46398. *Special Report* No, 19, 18 December 2018.
5. Esveld C. Recent developments in high-speed track. *1st Int. Conf. on Road and Rail Infrastructure*. University of Zagreb Zagreb 2010.
6. Zhai W, Wang K, Cai C. Fundamentals of vehicle–track coupled dynamics. *Vehicle System Dynamics*, 2009; **47**:1349–76.

7. He X, Wu T, Zou Y, *et al*. Recent developments of high-speed railway bridges in China. *Structure and Infrastructure Engineering*, 2017; **13**:1584–95.
8. Li P, Zhao Y, Zhou X Displacement characteristics of high-speed railway tunnel construction in loess ground by using multi-step excavation method. *Tunnelling and Underground Space Technology*, 2016; **51**:41–55.
9. Dai G-l, Liu W-s. Applicability of small resistance fastener on long-span continuous bridges of high-speed railway. *Journal of Central South University*, 2013; **20**:1426–33.
10. Krylov VV. Generation of ground vibrations by superfast trains. *Applied Acoustics*, 1995; **44**:149–64.
11. Madshus C, Kaynia A. High-speed railway lines on soft ground: Dynamic behaviour at critical train speed. *Journal of Sound and Vibration*, 2000; **231**:689–701.
12. Ren X, Wu J, Tang Y, *et al*. Propagation and attenuation characteristics of the vibration in soft soil foundations induced by high-speed trains. *Soil Dynamics and Earthquake Engineering*, 2019; **117**:374–83.
13. Garcia CR, Lehner A, Strang T, *et al*. Comparison of collision avoidance systems and applicability to rail transport. *2007 7th International Conference on ITS Telecommunications*, 2007, June, pp. 1–6.
14. Hu H, Tang B, Gong X, *et al*. Intelligent fault diagnosis of the high-speed train with big data based on deep neural networks. *IEEE Transactions on Industrial Informatics*, 2017; **13**:2106–16.
15. Pankovits P, Ployard M, Pouget J, *et al*. Design and operation optimization of a hybrid railway power substation. *2013 15th European Conference on Power Electronics and Applications (EPE)*, 2013, Sept., pp. 1–8.
16. Aguado JA, Racero AJS, de la Torre S. Optimal operation of electric railways with renewable energy and electric storage systems. *IEEE Transactions on Smart Grid*, 2018; **9**:993–1001.
17. Liu Y, Chen M, Lu S, *et al*. Optimized sizing and scheduling of hybrid energy storage systems for high-speed railway traction substations. *Energies*, 2018; **11**, https://doi.org/10.3390/en11092199.
18. Han Z, Zhang Y, Liu S, *et al*. Modeling and simulation for traction power supply system of high-speed railway. *2011 Asia-Pacific Power and Energy Engineering Conference*, 2011, March, pp. 1–4.
19. He Z, Zheng Z, Hu H. Power quality in high-speed railway systems. *International Journal of Rail Transportation*, 2016; **4**:71–97.
20. He X, Shu Z, Peng X, *et al*. Advanced cophase traction power supply system based on three-phase to single-phase converter. *IEEE Transactions on Power Electronics*, 2014; **29**:5323–33.
21. Hu H, He Z, Wang K, *et al*. Power-quality impact assessment for highspeed railway associated with high-speed trains using train timetable—part ii: Verifications, estimations and applications. *IEEE Transactions on Power Delivery*, 2016; **31**:1482–92.
22. Pascoe RD, Eichorn TN. What is communication-based train control? *IEEE Vehicular Technology Magazine*, 2009; **4**:16–21.
23. Caramia P, Lauro G, Pagano M, *et al*. Automatic train operation systems: A survey on algorithm and performance index. *2017 AEIT International Annual Conference*, 2017, Sep., pp. 1–6.
24. Scheepmaker GM, Goverde RM, Kroon LG. Review of energy-efficient train control and timetabling. *European Journal of Operational Research*, 2017; **257**:355–76.
25. Zimmermann A, Hommel G. Towards modeling and evaluation of ETCS real-time communication and operation. *Journal of Systems and Software*, 2005; **77**:47–54. Parallel and distributed real-time systems.
26. Ning B, Tang T, Qiu K, *et al*. CTCS—chinese train control system. *WIT Transactions on The Built Environment*, 2004; **74**, doi.10.2495/CR040401. https://www.witpress.com/elibrary/wit-transactions-on-the-built-environment/74/12130.
27. Bisheng He SH, Song R, Xu Y. Highspeed rail train timetabling problem: A time-space network based method with an improved branch-andprice algorithm. 2014; 15.
28. UIC Passenger Department. High speed traffic in the world. 2020. https://uic.org/IMG/pdf/20200127_high_speed_passenger_km.pdf (10 June 2020, date last accessed).
29. Russell SJ, Norvig P, *Artificial Intelligence: A Modern Approach*. Pearson Education Limited, h4th dE., Englewood Cliff, Prentice Hal, 2020, p. 31., 2020
30. Nau D, Ghallab M, Traverso P. *Automated Planning: Theory & Practice*. San Francisco, CA: Morgan Kaufmann Publishers Inc., 2004.
31. Niu H, Tian X, Zhou X. Demand-driven train schedule synchronization for high-speed rail lines. *IEEE Transactions on Intelligent Transportation Systems*, 2015; **16**:2642–52.
32. Liang K, Qin N, Huang D, *et al*. Convolutional recurrent neural network for fault diagnosis of high-speed train bogie. *Complexity*, 2018; **2018**, https://www.hindawi.com/journals/complexity/2018/4501952/.
33. Ghoseiri K, Szidarovszky F, Asgharpour MJ. A multi-objective train scheduling model and solution. *Transportation Research Part B: Methodological*, 2004; **38**:927–52.
34. Niu H, Zhou X, Gao R. Train scheduling for minimizing passenger waiting time with timedependent demand and skip-stop patterns: Nonlinear integer programming models with linear constraints. *Transportation Research Part B: Methodological*, 2015; **76**:117–35.
35. Jiang F, Cacchiani V, Toth P. Train timetabling by skip-stop planning in highly congested lines. *Transportation Research Part B: Methodological*, 2017; **104**:149–74.
36. Yue Y, Wang S, Zhou L, *et al*. Optimizing train stopping patterns and schedules for high-speed passenger rail corridors. *Transportation Research Part C: Emerging Technologies*, 2016; **63**:126–46.
37. Cadarso L, Marín A, Espinosa-Aranda JL, *et al*. Train scheduling in high speed railways: Considering competitive effects. *Procedia – Social and Behavioral Sciences*, 2014; **162**:51–60.
38. Sels P, Dewilde T, Cattrysse D, *et al*. Reducing the passenger travel time in practice by the automated construction of a robust railway timetable. *Transportation Research Part B: Methodological*, 2016; **84**:124–56.
39. Semet Y, Schoenauer M. An efficient memetic, permutation-based evolutionary algorithm for real-world train timetabling. *2005 IEEE Congress on Evolutionary Computation*, 2005, Sept, pp. 2752–9, Vol. **3**.
40. Cacchiani V, Huisman D, Kidd M, *et al*. An overview of recovery models and algorithms for realtime railway rescheduling. *Transportation Research Part B: Methodological*, 2014; **63**:15–37.
41. Lusby RM, Larsen J, Bull S. A survey on robustness in railway planning. *European Journal of Operational Research*, 2018; **266**:1–15.
42. Kamandanipour K, Nasiri MM, Konur D, *et al*. Stochastic data-driven optimization for multi-class dynamic pricing

and capacity allocation in the passenger railroad transportation. *Expert Systems with Applications*, 2020; **158**:113568.
43. Wu X, Qin J, Qu W, *et al.* Collaborative optimization of dynamic pricing and seat allocation for high-speed railways: An empirical study from China. *IEEE Access*, 2019; **7**:139409–19.
44. Sun Y, Jiang Z, Gu J, *et al.* Analyzing high speed rail passengers' train choices based on new online booking data in China. *Transportation Research Part C: Emerging Technologies*, 2018; **97**:96–113.
45. Antsaklis PJ, Passino KM, Wang SJ. An introduction to autonomous control systems. *IEEE Control Systems Magazine*, 1991; **11**:5–13.
46. Hwang H-S. Control strategy for optimal compromise between trip time and energy consumption in a high-speed railway. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 1998; **28**:791–802.
47. Sun Y, Cao C, Wu C. Multiobjective optimization of train routing problem combined with train scheduling on a high-speed railway network. *Transportation Research Part C: Emerging Technologies*, 2014; **44**:1–20.
48. Sun S, Li Y, Xu H Energy consumption optimization for high-speed railway based on particle swarm algorithm. *2012 Fourth International Conference on Computational Intelligence and Communication Networks*, 2012, Nov, pp. 879–82.
49. Lu S, Hillmansen S, Ho TK, *et al.* Single-train trajectory optimization. *IEEE Transactions on Intelligent Transportation Systems*, 2013; **14**:743–50.
50. Sicre C, Cucala A, Fernández-Cardador A. Real time regulation of efficient driving of high speed trains based on a genetic algorithm and a fuzzy model of manual driving. *Engineering Applications of Artificial Intelligence*, 2014; **29**:79–92.
51. Ji H, Hou Z, Zhang R. Adaptive iterative learning control for high-speed trains with unknown speed delays and input saturations. *IEEE Transactions on Automation Science and Engineering*, 2016; **13**:260–73.
52. Song Y, Song W. A novel dual speedcurve optimization based approach for energy-saving operation of high-speed trains. *IEEE Transactions on Intelligent Transportation Systems*, 2016; **17**:1564–75.
53. Yang H, Zhang K, Liu H. Online regulation of high speed train trajectory control based on T-S fuzzy bilinear model. *IEEE Transactions on Intelligent Transportation Systems*, 2016; **17**:1496–508.
54. Travel C. World's first 350km-perhour driverless bullet train goes into service in China. 2020. https://edition.cnn.com/travel/article/driverless-bullet-train-china/index.html (15 June 2020, date last accessed).
55. Chen Z, Wang Y. Impacts of severe weather events on high-speed rail and aviation delays. *Transportation Research Part D: Transport and Environment*, 2019; **69**:168–83.
56. Dong P, Zheng T, Du X, *et al.* SVCC-HSR: Providing secure vehicular cloud computing for intelligent high-speed rail. *IEEE Network*, 2018; **32**:64–71.
57. Gong P, Cao Y, Cai B, *et al.* Multiinformation location data fusion system of railway signal based on cloud computing. *Future Generation Computer Systems*, 2018; **88**:594–8.
58. Rajkumar RI, Sundari G. Intelligent computing hardware for collision avoidance and warning in high speed rail networks. *Journal of Ambient Intelligence and Humanized Computing*, 2020; 1–13.
59. Fraga-Lamas P, Fernández-Caramés TM, Castedo L. Towards the internet of smart trains: A review on industrial iot-connected railways. *Sensors*, 2017; **17**:1457.
60. Lee J, Ni J, Djurdjanovic D, *et al.* Intelligent prognostics tools and e-maintenance. *Computers in Industry*, 2006; **57**:476–89. E-maintenance Special Issue.
61. Liu Z, Jin C, Jin W *et al.* Industrial ai enabled prognostics for high-speed railway systems. *2018 IEEE International Conference on Prognostics and Health Management (ICPHM)*, 2018, June, pp. 1–8.
62. Vichare NM, Pecht MG. Prognostics and health management of electronics. *IEEE Transactions on Components and Packaging Technologies*, 2006; **29**:222–229.
63. Wang Q, He Z, Feng D. A maintenance mode decision method for traction power supply system of high-speed railway. *2015 IEEE Conference on Prognostics and Health Management (PHM)*, 2015, June, pp. 1–7.
64. Lin B, Wu J, Lin R, *et al.* Optimization of high-level preventive maintenance scheduling for high-speed trains. *Reliability Engineering System Safety*, 2019; **183**:261–75.
65. Thaduri A, Galar D, Kumar U. Railway assets: A potential domain for big data analytics. *Procedia Computer Science*, 2015; **53**:457–67. INNS Conference on Big Data 2015 Program San Francisco, CA, USA 8–10 August 2015.
66. Xie J, Li T, Yang Y, *et al.* Learning features from high speed train vibration signals with deep belief networks. *2014 International Joint Conference on Neural Networks (IJCNN)*, 2014, July, pp. 2205–10.
67. Guo C, Yang Y, Pan H, *et al.* Fault analysis of high speed train with dbn hierarchical ensemble. *2016 International Joint Conference on Neural Networks (IJCNN)*, 2016, July, pp. 2552–9.
68. Feng D, Lin S, He Z, *et al.* A technical framework of phm and active maintenance for modern high-speed railway traction power supply systems. *International Journal of Rail Transportation*, 2017; **5**:145–69.
69. Chen H, Jiang B, Lu N. Data-driven incipient sensor fault estimation with application in inverter of high-speed railway. *Mathematical Problems in Engineering*, 2017; **2017**.
70. Feng H, Jiang Z, Xie F, *et al.* Automatic fastener classification and defect detection in vision-based railway inspection systems. *IEEE Transactions on Instrumentation and Measurement*, 2014; **63**:877–88.
71. Aytekin C, Rezaeitabar Y, Dogru S, *et al.* Railway fastener inspection by real-time machine vision. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 2015; **45**: 1101–7.
72. Lee J, Lee K-C, Lee Y-J. Long-term deflection prediction from computer vision-measured data history for high-speed railway bridges. *Sensors*, 2018; **18**, https://doi.org/10.3390/s18051488.
73. Aydin I, Karaköse E, Karaköse M, *et al.* A new computer vision approach for active pantograph control. *2013 IEEE INISTA*, 2013, June, pp. 1–5.
74. Han Y, Liu Z, Lee D, *et al.* Computer vision–based automatic rod-insulator defect detection in high-speed railway catenary system. *International Journal of Advanced Robotic Systems*, 2018; **15**: doi.org/10.1177/1729881418773943.
75. Zhu X, Gao X, Wang Z, *et al.* Study on the edge detection and extraction algorithm in the pantographslipper's abrasion. *2010 International Conference on Computational and Information Sciences*, 2010, Dec, pp. 474–7.
76. Ryo Furutani NM, Kudo F. Case study of energy efficiency in railway operations – utilization of ai in the railway sector. 2016. http://www.hitachi.com/rev/archive/2016/r2016_06/105/index.html (7 January 2019, date last accessed).
77. D-RAIL. D-rail keeping track. 2020. https://www.d-rail.com/#details (15 June 2020, date last accessed).