IEEE Access
Multidisciplinary ⁝ Rapid Review ⁝ Open Access Journal

Received July 30, 2019, accepted August 9, 2019, date of publication August 13, 2019, date of current version August 29, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2935106

Train Dispatching Management With Data-Driven Approaches: A Comprehensive Review and Appraisal

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This work was supported in part by the National Natural Science Foundation of China under Grant 71871188 and Grant U1834209, in part by the State Key Laboratory of Rail Traffic Control and Safety under Grant RCS2019K007, and in part by the Open Research Fund for National Engineering Laboratory of Integrated Transportation Big Data Application Technology under Grant CTBDAT201909.

ABSTRACT Train dispatching (TD) is at the forefront of all rail operations that transport passengers or goods. Recent technological advances and the explosion of digital data have introduced data-driven methods (DDMs) in rail operations. In this study, DDMs on the TD problem are briefly explored, focusing on relevant studies on delay distribution, delay propagation, and timetable rescheduling. Data-driven TD methods, including statistical methods (SM), graphical models (GM), and machine learning (ML) methods are reviewed. Then, key issues in establishing different data-driven models for the TD problem are addressed. Subsequently, ML methods are considered to be among the most promising DDMs that lead to innovative TD methods, relying on rich data obtained from train operations. This study emphasizes the potentials for designing new alternatives in the three key fields of interest and provides directions for further research on TD. Future research, including the ML-driven TD and intelligent TD, were discussed in this study.

INDEX TERMS Data-driven, delay distribution, delay propagation, timetable rescheduling, train dispatching, machine learning.

I. INTRODUCTION

Robust train operations and effective management of unexpected incidents are critical for quality of service (QoS) and the competitiveness of rail services in the transportation sector. Delays affect users' expectations about reliability, punctuality, and QoS. Moreover, delays cause missing transfers and extend working hours of crews and locomotives, thereby leading to increased operational cost for operators. Consequently, rail operating companies are given high priority in avoiding and reducing the negative influence of delays [1] . A significant number of models and algorithms have been proposed to improve train services in response to unexpected incidents in rail operations [2]. Recently, several railway traffic control (RTC) projects were launched to improve train operations and services for the ever-increasing rail travel demand. The Europe ON-TIME project, which began in November 2011, defines two out of eight targets mainly related to disturbance management [3]. The project titled Safety, Reliability, and Disruption Management of High-Speed Rail (HSR) and Metro Systems (Grant No. T32-101/15-R) was granted to enable dependable train operation, performance, and service through the advanced design of rail system operations with the help of train operation data [4]. In case of a delay incident, a train dispatcher who is responsible for facilitating the train movements over an assigned territory follows a set of dispatching decisions that are provided in the timetable or adjust them according to critical decisions. Train dispatching (TD) is a multi-criteria decision-making (MCDM) problem [5], [6]. Although several MCDM approaches are available, each has its advantages and disadvantages. As reviewed in [7], [8],

The associate editor coordinating the review of this article and approving it for publication was Yuedong Xu.

TD has become an active research area mostly due to delay reduction priority. However, a gap remains in the number of models that can handle TD in a real-time RTC system. In addition, most of the proposed solutions are based on abstracted models and simplified assumptions. Most of the recent practices in TD are still dominated by predetermined rules, contingency plans, intuition, and personal expertise. In practice, dispatchers need to integrate real-time structured and unstructured information (supporting data) when making dispatching decisions in response to unexpected incidents and displaced operations. This phenomenon is the main limitation of conventional mathematical models because they can hardly handle real-world, large-scale models in real-time, thereby leaving aside the gap between the experimental results from these models and the actual operations.

Recent rapid advances in monitoring and communication systems and data technologies enabled a wide range of possibilities, such as data-driven train dispatching (DDTD) for operations management in rail transportation [9]. Train operation records from control and monitoring systems are a valuable resource to mine and assess realized operations to improve train operations based on data-driven decisions. The applications of big data in railway operations, maintenance, and safety have attracted the attention of researchers and practitioners [10]. Admittedly, data-driven decisions are remarkable, practical, and reasonable. In this regard, TD-related activities and decisions can be supported by hidden knowledge extracted from train operation records to make better decisions and actions in response to delay in future train operations.

The rest of this paper is organized as follows: In Section 2, we briefly introduce some related concepts of TD, and we present the collection of dispatching data and summarize dimensions that are reviewed. Subsequently, in Section 3, we categorize three types of data-driven models that have been applied in TD, covering 153 relevant papers focusing on data-driven methods (DDMs) in TD. Then, we presented the review results and discussed the future research direction and the potential applications of DDMs in TD in Section 4. Finally, we present conclusions in Section 5.

For reading convenience, all the abbreviations and their full forms in this paper are listed alphabetically in Table 1.

TABLE 1. Index of phrases have an abbreviation.

Full forms	Abbreviation
Artificial neural networks	ANN
Buffer Index	BI
Buffer time allocation optimization	BTA
Conflict detection	CD
Conflict detection and resolution	CDR
Convolutional Neural Networks	CNNs
Conflict resolution	CR
Centralized Traffic Control	CTC
Deep Belief Networks	DBNs
Data-driven methods	DDMs
Data-driven train dispatching	DDTD
Deep extreme learning machines	DELM
Deep learning	DL
Designer of Network Schedules	DONS
Deep Reinforcement Learning	DRL
Data-driven dynamic train delay prediction system	DTDPS
Extreme Learning Machine	ELM
Fuzzy Petri net	FPN
Graphical models	GM
High-Speed Rail	HSR
Linear Programming	LP
Least square method	LSM
Least square support vector machine	LSSVM
Multilevel Advanced Railways Conflict resolution and Operation	MARCO
Multi-Criteria Decision Making	MCDM
Machine learning	ML
Neural Networks	NN
Non-Parametric Bayesian Network	NPBN
Passenger information control system	PIC
Quality of service	QoS
Recurrent Neural Networks	RNN
Railway traffic Optimization using Alternative graphs	ROMA
Railway traffic control	RTC
Real-world train operation data	RWTOD
Schweizerische Bundesbahnen	SBB
Statistical methods	SM
Support vector machine	SVM
Support vector regression	SVR
Train dispatching	TD
Train Delay Prediction Systems	TDPS
Traffic Management System	TMS
Train Observation and Tracking System	TROTS
Timetable rescheduling	TTR
Weighted Average Distance	WAD

II. DATA-DRIVEN TRAIN DISPATCHING

A. TRAIN DISPATCHING

A train dispatcher (United States, Japan, and China), rail traffic controller (Canada), train controller (Australia), or signalman (United Kingdom) is obliged to make real-time decisions to command trains. For the sake of safety and efficiency, train operations are governed by strict rules. Once delay occurs, the operations should be recovered as soon as possible at the first possible position with the greatest care to avoid risking the subsequent operations. Thus, dispatchers should make critical dispatching decisions on the basis of available data and previous experiences. First, they need to collect relevant data from operational circumstances. Second, they need to process the data to gather useful information. Third, dispatching knowledge and personal experiences lead to decisions in train operation dispatching strategies. Traditional dispatching works are highly experience-oriented, thereby resulting in many uncertainties and inconsistencies in decision making in response to similar circumstances. Although the proposed mathematical models for TD perform well in experiments and provide remarkable results in the academic field, their application in real-time TD situations is difficult because they cannot consider the knowledge and expertise of dispatchers. This phenomenon is mainly due to the hidden factors and interdependencies that models can hardly cover, but a dispatcher can consider.

B. TRAIN DISPATCHING DATA

Recent technological advances and developments in rail transportation have enabled operators to store, access, and mine enormous real-world train operation data (RWTOD) from realized train processes. These kinds of RWTOD can come in three forms. The first form is structured data (e.g., arrival and departure time at stations), which is mainly reserved in the centralized traffic control (CTC) system [11]. The second form is semi-structured data, which can be mined from recorded videos, images, and event notes [12], [13]. The third form is unstructured data (e.g., dispatching command and other literal event records), which can be captured by monitoring systems. Researchers and practitioners can use a host of data processing tools to process the numeral structured data. However, semantic and syntactic data models, which offer greater capabilities for data integration, extensibility, and compatibility over traditional approaches, are often applied to process semi-structured and unstructured data [14]. Train operation appearance is analyzed and estimated to a certain extent using train operation records of the Japanese railway, whether in the form of tables, texts, graphs, images, and videos [15]. Goverde and Hansen confirm that delay propagation and conflicts in the Netherlands can be analyzed by using train operation records [16]. Graffagnino visualizes train operation data in Switzerland to study delays [17]. For instance, TRENO in OPEN TRACK performs an extremely detailed graphical analysis of train movements, train speeds, acceleration, braking curves, and dwell times using RWTOD tools [18]. Moreover, train operation data in other countries, such as Germany [19], Italy [20], Denmark [21], Finland [22], UK [23], Japan [24], India [25], Turkey [26], US [27], Serbia [28], and China [29], [30], have been used in data-driven TD modeling.

C. DATA-DRIVEN TRAIN DISPATCHING ISSUES

1) DELAY DISTRIBUTIONS

Train operations are assumed to be stochastic processes [26]. Dispatchers need to capture the characteristics of delays on specific lines or local railway network. Delay distributions usually provide basic rules on delay causes that the trains follow and assist dispatchers in obtaining the delay probabilities and duration online and offline. Figure 1 shows the decision making based on delay distribution models, which may include delay cause distributions, arrival/departure delays at stations, running time delays in sections, delay aggregation distributions, and delay influence distributions. The upper part outlines what dispatchers do, and the lower part illustrates some delay distribution examples at stations and in sections. Overall, dispatchers need to estimate the potential delay probabilities and their influences based on delay-specific causes according to historical delay distributions in the approaching journey. When a delay occurs to a train, various strategies, such as adjusting running speeds, altering dwell times, and changing overtaking could be considered by dispatchers to absorb delays.

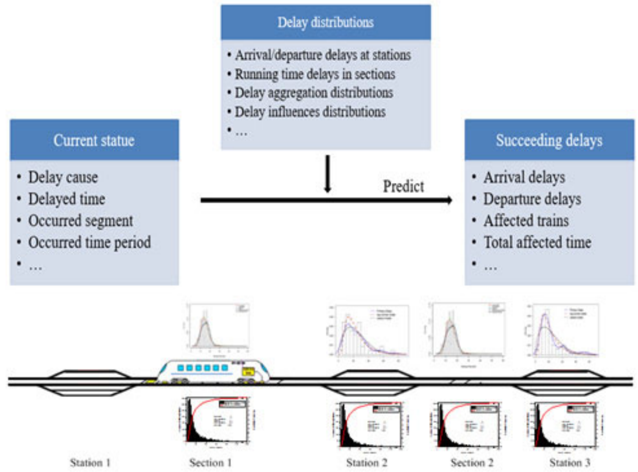

FIGURE 1. Decision-making based on delay distributions.

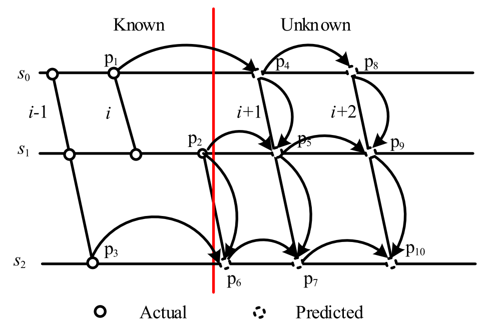

FIGURE 2. Recursive iterative processes of delay prediction.

2) DELAY PROPAGATION

Delay propagation is a function of delay aggravation caused by disturbances and delay recovery activities conducted by dispatchers. A delay may spread out in vertical and horizontal orientations, leading to delay propagation on the line or even on the network and contributing to the complexities of train operations. Delay propagation has been the main source of displacements in the railway system; thus, minimizing delay propagation takes high priority [31]. Analyses of microscopic and macroscopic approaches show that most of the studies consider the railway system at a microscopic rather than at a macroscopic level, and almost all papers have focused on minimizing delays of passengers or freight. Delay prediction is one of the most popular issues in these studies. It is a typical data-driven process because the following arrival or departure time is subject to its current status and the adjacent leading train. Thus, dispatchers can determine the arrival and departure times one after another. Figure 2 shows that determining train status is a recursive, iterative process. The time axis (red line) denotes the current time, and dispatchers need to use known data on the left of the time axis to predict unknown events on the right of the time axis. The origination departure time p_4 of train $i+1$ is determined by p_1, and p_5 is derived by p_2 and p_4. Similarly, p_7 is derived from p_5 and p_6. Train $i+1$ is

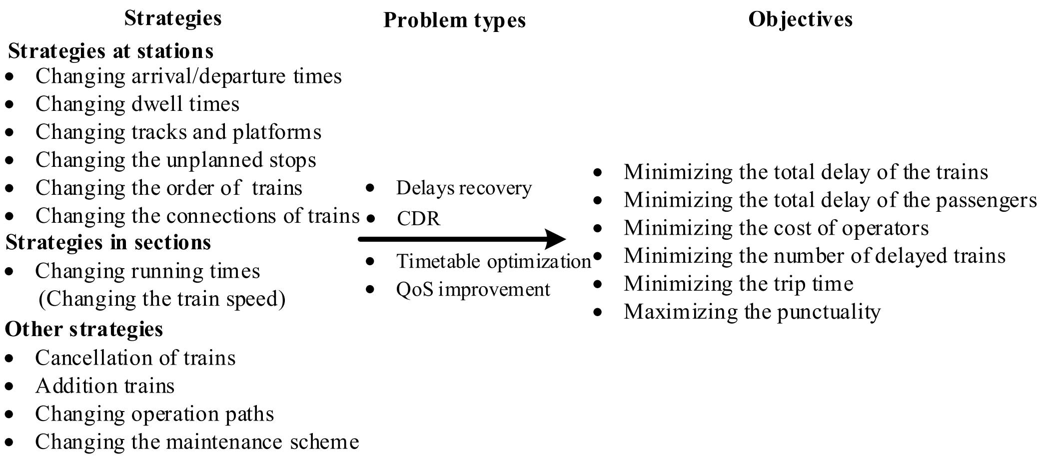

FIGURE 3. Strategies and objectives of timetable rescheduling.

mostly subject to the status of train i, whereas train $i+2$ is mostly subject to the status of train $i+1$, whose predicted points of p_4, p_5, and p_7 are considered historical data. Major disturbances can propagate to other trains in the network, thereby requiring short-term adjustments in the timetable to limit delay propagation [32].

3) TIMETABLE RESCHEDULING

TTR is what dispatchers mainly deal when the effect of unexpected displacements on train operations are adjusted. TTR is usually considered the decision of altering succeeding train arrival, departure, and running times, which are previously planned timetable. CD and resolution CDR, minimizing delays, minimizing delay costs, and BTA optimization are the mainly proposed objectives in TTR. Figure 3 summarizes the strategies that are mainly used by dispatchers and proposed objectives in TTR in the existing literature.

Several problems, such as delay recovery, conflict detection and resolution, timetable optimization, and QoS improvements, are investigated as the main issues of TTR. Fang *et al.* [33] survey nine types of models and solution approaches on TTR in railway networks, addressing problems of CR, disturbance/disruption recovery, TD, and some data-driven associated methods in general. A review of recovery models and algorithms for real-time railway rescheduling of recent decades can be found in the work of Cacchiani *et al.* [7]. Here, the most recent papers on the DDMs employed in TTR are specifically considered.

When delays occur, the main problem that dispatchers focus on is CDR because the delay of only one train may cause an entire cascade of delays to other trains over the entire railway network and further delays and conflicts at train interactions and transferring points [34], [35]. The delays may lead to conflicts due to the competition of resources, and conflicts tend to lead to delays because of the time loss and the hindrance between trains. Conflict chains and trees should be prevented by dispatchers [36]. A conflict occurs when an overlap occurs between two or more time windows due to deviations of train events [37]. The total solutions for trunk lines in European railway networks include identifying and resolving conflicts automatically are the bases of the European Rail Traffic Management System [38]. One of the ultimate goals of TTR is CR, of which the detailed loop is presented in [39], and the detailed loop of CD is proposed by [40].

In practice, a certain amount of buffer times is mostly added to the timetable. However, this method can affect operational capacity in heavily utilized networks by contributing to longer travel times. Furthermore, the unused buffer times in sections (or stations) cannot be used by trains in the downstream sections (or stations) due to its non-storage property. Therefore, various BTA schemes can have different impacts on delay propagation and recovery and the operational capacity of the railway system, even with the same amount of buffer time [41]. To this end, two main issues need to be addressed. The first issue is how and to which extent the buffer times affect delay recovery and CR. The second issue is how to distribute the buffer time among different stations and sections to achieve the highest utilization ratio of buffer time. The timetable planners and dispatchers design or reschedule timetables with historical data using the empirical buffer times used in previous timetables with certain delay scenarios. On the one hand, planners may create a new BTA scheme for a new operation based on the statistics of historical timetables that are used for the line. They may use the statistics of timetables of another line with similar operating conditions for a newly opened line. This process can be considered a long-run period BTA to boost the robustness of the timetable. On the other hand, dispatchers adjust timetables according to the historical performance of a certain day to resolve probable delays or conflicts. This process can be considered a short-term BTA.

D. OUTLINE OF DATA-DRIVEN TRAIN DISPATCHING ISSUES

DDMs or data-oriented and data-based models are built by analyzing the actual data obtained from an operating system, particularly in finding connections between the subsystems

TABLE 2. Case studies on train dispatching.

Literature	Country	Data	Addressed issues	Methodologies or systems
[19]	Germany	Train position data Arrival and departure time	Delay distribution, Evaluation of timetable quality	Open Timetable
[21]	Denmark	Train delay records	Assess and layout of timetable supplements	Statistical methods
[22]	Finland	Train actual timetable	Delay chains	Data-mining approach
[23]	The UK	Train delay data Meteorological data	Impacts and propagation of disruption	Statistical methods, Visualization
[24]	Japan	Train actual timetable	Delay causes Delay distributions	Visualization
[25]	India	Track occupation data Train actual timetable	Robustness evaluating of railway networks	Stochastic delay propagation models
[26]	Turkey	Train actual timetable	Train states and steady-state delay probabilities estimation	Markov chain model
[27]	USA	Freight data Train operation records	Optimization of rail capacity and congestion.	Statistical methods
[28]	Serbia	Track occupation data Train actual timetable	Estimating train delays	Fuzzy Petri net
[29]	China	Train actual timetable of HSR	Delay distribution models	Statistical methods Regression models
[31]	Netherlands	Track occupation data Train delays	Short-term traffic prediction	ROMA dispatching system
[36]	Netherlands	Track occupation data Train actual timetable	Dispatching decisions Delay propagation chain	TNV-Conflict TNV-Statistics
[47]	Netherlands	Track occupation data Train actual timetable	Train delay propagation prediction	Analytical model
[48]	Netherlands	Track occupation data Train timetable	Knock-on delays estimation	Analytical stochastic model
[49]	Germany	Train actual timetable	Delay Dependencies, delay propagation	Correlation statistics
[50]	Denmark	Train position data Train actual timetable	Analysis of train deviations	Punctuality Reporting System
[51]	China	Train actual timetable of HSR	Primary delay recovery	Regression model Random forest model

and state variables (input, internal, and output variables) without requiring many details and explicit knowledge from the physical behavior of the system. DDMs have strong modeling abilities for complex systems, digging out relationships among system indices and establishing models that can fit different situations [42]. The survey shows that DDMs are multifunctional and are important in the development of intelligent transportation systems [43].

The rail industry has been a pioneer in using and implementing big data analytics. In this regard, the recently published book on big data application has shown practical aspects of DDMs in rail transportation [44]. The RWTOD has been widely used in many countries, supporting the improvement of rail traffic control qualities. For example, a data-driven train delay prediction system is developed with the help of big data analytics [20]. In Table 2, some of the case studies on TD issues based on the RWTOD in typical countries are summarized. Some trained models based on RWTOD have been used in many simulations in the last decade via commercial software, such as Opentrack [45] and RailSys [46], and laboratory software, such as railway traffic optimization using alternative graphs (ROMA) [31] and TNV-Conflict [36], to figure out the precise behavior of trains and improve train operation qualities.

Turner *et al.* [52] reviewed some studies on timetable planning and scheduling that applied DDMs, such as data mining, knowledge engineering, and expert systems. In this work, we look into the most popular DDMs, namely, statistical method (SM), Graphical models (GM), and machine learning (ML) methods [42]. The SM, including correlation analysis, regression models, and visualization methods, mine relationships among variables embedded in the data. The GM methods attempt to derive knowledge or rules from the data to establish the arc weights of the alternative graphs, the matrices of the Markov model, the probability chains of the Bayesian network, and the fuzzy numbers of the fuzzy network. These models include fuzzy logic, expert, and probabilistic graphical models. ML is a method used to produce reliable, repeatable decisions and to uncover hidden knowledge by learning from relationships and trends in historical datasets. The support vector machine (SVM), reinforced learning, deep learning (DL), and artificial neural networks (ANN) are also typical ML methods. Figure 4 shows that three different key subjects in TD, including delay

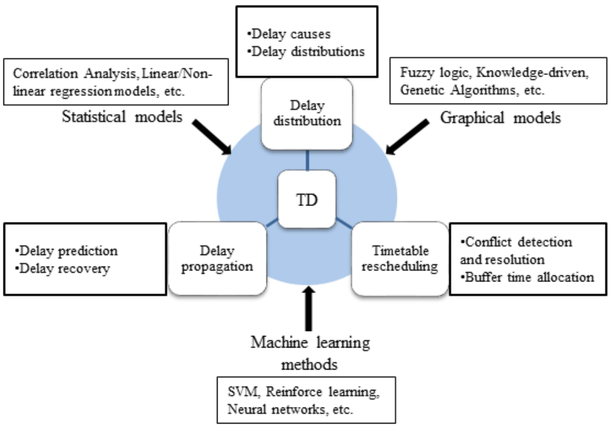

FIGURE 4. Outline of data-driven train dispatching issues.

distributions, delay propagation, and TTR and optimization, are reviewed using the aforementioned DDMs.

III. DATA-DRIVEN MODELS IN TRAIN DISPATCHING: LITERATURE

A. DATA-DRIVEN DELAY DISTRIBUTIONS: LITERATURE

In this section, we review studies on delay causes and distributions based on DDMs. Train delay distributions highly depend on the varying operating conditions of specific lines and networks. Although developing universal distributional forms that can be applied everywhere is difficult, data from specific lines can be used to reveal the general principles for other similar areas. Conte [53] pioneered the systematic study of dependencies among delays using data-based methods; his application-oriented thesis deals with identifying dependencies among delays through a stochastic analysis based on the measured arrival and departure delays that have been considered observations of random variables.

1) DELAY CAUSES

a: SM

Observations show that external factors are the main causes of primary delays, and operation interference is the main cause of knock-on delay, according to the data of on-schedule ratios. The number of passengers, occupancy ratio (passengers/seats), infrastructure utilization, cancellations, temporary speed reductions, railway construction, departure and arrival punctuality, and operational priority rules are the main factors that may affect train operations [54]. Palmqvist *et al.* [55] applied SM to quantify how severe weather, timetable, operational, and infrastructure-related variables can influence the punctuality of passenger trains.

From the aspect of external factors, poor weather condition has always been the main cause of primary delays. A novel exploration of the impacts of extreme events has been conducted [23], [56]. Punctuality statistics on the Norway railway show that more than 4000 delay hours, which was approximately 30% of the total amount of delay hours, was caused by infrastructure conditions [57].

Internal and congestion-related factors, such as crosses, passes, overtakes, prior time period train counts, total train hours, train spacing variability, and train departure headway were investigated by using SM for freight trains in the US [27]. The study found that the primary congestion factors (crosses, passes, and overtakes) consistently have the largest effect on congestion delay. Positive and statistically significant relationships between reactionary delays and capacity utilization conclude the exponential relationship between adding trains onto a congested network and capacity utilization, which is an important internal factor of delay [58].

The experience from Taiwan HSR shows that shortening the maintenance cycle can effectively alleviate the problem of train delay caused by signal failures [59]. Recently, over 1,200 train operation records were obtained from the ‘‘delay events record chart’’ of Wuhan–Guangzhou HSR in China, and seven categories of external causes that lead to primary delays are identified [29], and a similar relationship plot between capacity utilization and delays are also obtained from the Chinese HSR operation data. Statistics also show that almost 90% of disruptions are due to bad weather [60]. All these results help dispatchers to know the overall causes of delays in HSR.

Data-driven visualization based on train operation records can help determine delay causes. Timetable planners can intuitively determine the situation of train operation and obtain helpful information for analysis by visualizing the historical train operation data [24]. Chromatic Diagram, a helpful software to visualize the raw data, is abstracted and plotted to determine the delay causes [17], [61]. Moreover, the bubble diagram, incremental delay diagram, 3D diagram, and other information visualizations, such as box diagrams, dwell times, running times, headways, and scatter diagrams for delays, are applied to visualize historical train operation records [24]. Causes and effects of delay can be analyzed, and delay reduction measures can be evaluated by comparing results with the help of these skills.

b: GM

The fault trees are generally used for estimating the risk and development of railway facility failures. Port and Ramer [62] stated that fault trees might help estimate earthquake-induced failure probability and downtime of critical facilities, including in railway systems. Liu *et al.* [63] employed a fault tree combined with quantitative analysis to investigate the fault of HSR accidents. The fault tree analysis is also used to determine where the risks are, the dangers they pose, and what factors have the most significant effects on the rail system by analyzing all possible basic events. All wind-, rain-, and snow-related adverse weathers along with human-related factors, can potentially cause great risks. A hierarchical analytic process is used to calculate the weights among indices for each adverse weather factor. A fuzzy synthetic evaluation process is then conducted to identify the risk level of an evaluation target [64].

c: ML
ML is not popularly used in studies of delay causes. So far, large amounts of historical detector data together with failure events, maintenance action, inspection schedule, train type, and weather information are used to predict railway facility maintenance [65]. Several analytical approaches, including correlation analysis, causal analysis (e.g., principal component), time series analysis, and ML techniques (e.g., SVM), are applied to learn rules automatically and build failure prediction models. Oneto *et al.* [66] proposed a train delay prediction system (TDPS) using ML to predict delays, considering exogenous weather data. The model can be further improved by including data from exogenous sources, particularly on the weather information provided by national weather services. Results of real-world data from the Italian railway network show that the recommendations of this study can remarkably improve the current state-of-the-art train delay prediction system. The delay cause discovery model is constructed in four phases, including data preprocessing and analysis, decision tree based on ML methodology, delay analysis with key delay factors, and spatiotemporal lateness topology analysis [67].

2) DELAY DISTRIBUTIONS
a: SM
Several standard distribution models are often used to fit data-driven probability distributions and regression models. Delay elements, indices, and distributions can be easily observed using data-driven visualization methods. The chromatic diagram is used to visualize where a delay emerges and how it develops [68]. Then, dispatchers can easily identify the frequency and severity of delays and the effectiveness of the respective delay reduction measures. The proposed open timetable used in Schweizerische Bundesbahnen (SBB) helps railway timetable planners to evaluate actual schedule adherence data and assist dispatchers in identifying delays [19]. Delay distributions show the number of trains in various groups and different delay patterns using real data with clustering methods [69].

An estimation of the duration of disturbances using SM [70] or other sophisticated techniques usually happens in railway networks [71]. The third quarter distributions of actual running times and delays are investigated using historical data [21]. A percentile approach, which assists the punctuality reporting system of RDK to work effectively, helps dispatchers to aggregate delay percentiles on train numbers (or groups of trains), geography (measuring points), time period, percentile, or as a combination [50]. Several reports have been developed to help RDK locate systematic causes of delays. These approaches can be used to achieve improved punctuality. Furthermore, on the most important lines of RDK, aggregations of data for analysis of dynamics of delays and queuing effect on single lines between stations are investigated using the data from the digital CTC [72].

So far, delay disturbances of trains in most studies are approximated by an exponential distribution. A shifted exponential distribution for the free-running time of each train is proved, and the effect of headways on knock-on delays of trains is simulated in [73]. Goverde *et al.* [74] fitted the distributions of train arrival time, departure times, and dwell times in the Netherlands railway, and Yuan [75] investigated the departure and arrival times at Hague HS station with RWTOD. Both of their studies concluded that train operation interference time follows a negative exponential distribution. The exponential distributions, which are assumed for inter-arrival time and minimal headway times, are used in a queueing network model to predict the average waiting time of trains [76]. Later, Briggs and Beck [77] used the *q*-exponential function to demonstrate the distribution of train delays on the British railway network.

The Weibull, Gamma, and lognormal distributions have been adopted in several studies [78], [79]. Buker and Seybold [80] evaluated the suitability of a group of existing distribution models, such as modified exponential phase-type, theta-exponential, and polynomial distributions, to approximate arrival delays. The operation data from the Wuhan–Guangzhou HSR suggest that the probability density distribution of different disruption sources and distributions of affected trains due to delays are plotted in general [60]. The log-normal distribution can fit the primary delay duration distribution, and the inverse model can fit the affected number of train distributions [29], [81]. Also, the log-logistic probability density function is the best distributional form to approximate the empirical distribution of running times [82]. For the fitting models, several model test methods are applied, Kolmogorov–Smirnov test, for instance [60], [82], [83].

Similarly, punctuality data from automatic registrations in the signaling systems have been used for regression studies, and correlation coefficients are found to be significant at 0.01 level between arrival punctuality and the number of passengers, occupancy ratio, and departure punctuality [54]. The nonlinear regression model generated by train operation records is used to calculate the expected times under certain delays [73]. Specifically, the developed models can be incorporated into a dispatching decision support system to improve real-time train traffic control. This method would provide dispatchers with accurate estimates of the occurrence of possible disruptions and the potential effects of a given disruption event.

b: GM
Train operations were described by a set of processes, including train running, dwell, and waiting times caused by conflicting train routes, in which dependencies between events and processes are graphically represented by timed event graphs [84]. The running and dwell time and headway arcs are all generated by sorting all events using the same train number of their date and time of occurrence, containing all arc modeling delay dependencies among events. Furthermore, arc weights that reflect the minimal time between two adjacent events have been derived by calculating a small percentile of all observed arc weights in the track occupation data.

Zilko *et al.* [85] developed a probabilistic model to estimate the railway disruption duration using non-parametric Bayesian network (NPBN), which strongly depends on the empirical distributions of each dependent variables that were generated by historical data in the entire Dutch railway network. However, the Bayesian network strongly relies on the accuracy of the information, which updates over time.

c: ML

So far, papers dedicated to studying delay distributions using ML methods are limited. An ML method is proposed for the automatic calibration of disturbance parameters for railway operation simulation to generate stochastic disturbances. Supported by ML, efforts toward calibrating parameters have been greatly reduced with ensured consistency between simulation models and actual railway operations [86]. The proposed calibration algorithm has been implemented and integrated into the new simulation software, DoSim. A remarkable improvement in system performance is observed. The software has been tested on an example for a real railway network in Germany with 71 stations. The recently published paper in TRB meeting presents statistical and ML models to build the relation between delay duration and cause and statistically predict delay time [87]. The models of MLR, decision tree, and SVM are applied, in which SVM performs best in estimation accuracy. Also, the SVM models are applied to investigate the relationship between the primary delays and their affected trains based on the train operation records obtained from Guangzhou Railway Bureau in China, and the ε-SVR and υ-SVR models show remarkable performance to predict the possibilities of the number of affected trains [88].

3) STATE-OF-THE-ART ON DELAY DISTRIBUTIONS

This is not an easy task for dispatchers given their heavy workload. The delay information should be provided with an easy-to-understand way so that the information can be used without increasing hassle. Delay distributions and relationships between delays and their causes help manage delays during train operations. They can help dispatchers to understand the delay mechanism to improve the management of train delays in practice. Table 3 presents a summary of the literature on data-driven delay distributions.

The actual operation can be affected by various of factors, over 50 broad attributable reasons have been listed in the UIC 450-2 that will lead to train delays, such as weather, facility failure, and drivers' and travelers' behavior [89]. The reviewed studies have shown the roadmap of modeling delay distributions based on RWTOD (Figure 5). Two layers of indices obtained from RWTOD should be used in the modeling. First, dual-index models should combine delay causes and one of the indices in the "second layer indices." Second, multi-index models can be formed using several or all indices that can be obtained. In this light, spatiotemporal delay distribution models, delay aggravation, and recovery distribution models, as well as comprehensive models that involve all the elements above, can be established. ML methods should be employed because more data have become available, and the big data have provided a broad vision in data mining.

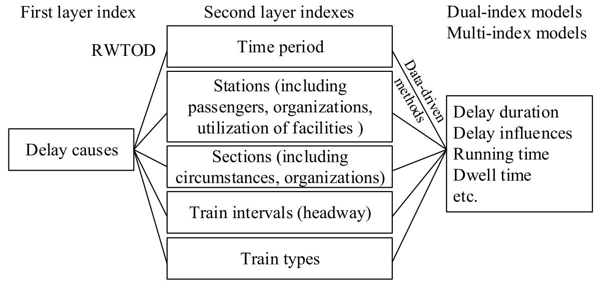

FIGURE 5. Roadmap of the data-driven approach for delay distribution modeling.

The existing studies have four deficiencies concerning delay distributions, which are:

(1) Researchers have focused on delay-distribution modeling based on specific lines, lacking general models that can fit multiple lines.
(2) Cause-based models of delays are scarce; many specific causes for which the data can not be obtained have not been studied. More detailed relationships between delay distributions and their causes based on rich RWTOD should be determined. As stated by the International Union of Railways, the availability of delay causes is urgently required to optimize international train networks [21]. Primary and secondary delays should be explicitly recorded, thereby making the development of algorithms possible to link primary and secondary delays and to determine how delays develop and how trains may auto-correlate their delays.
(3) The studies tend to focus on a single line or even a segment. It is necessary to study the delay distributions for the entire railway network involving many types of trains, especially the systems comprised of cross-line trains.
(4) The models can fit the delay data well, but they can not tell us the mechanisms causing the delays. Also, most of the statistic models need to be established based on some prior assumptions.

B. DATA-DRIVEN DELAY PROPAGATION: LITERATURE

Delay prediction and recovery are the main issues in addressing the problem of delay propagation. Delay propagation factors, such as interaction among primary delays, knock-on delays, exogenous events, delay aggravation, and recovery can be approximated using probability functions that can consider factors from sections, stations, time, and train interactions.

1) DELAY PREDICTION

Train operations are highly dependent on running and dwell time variations [90]. The estimation of running times requires predicting the effect of disturbances and subsequent buffer

TABLE 3. Summary of the State-of-the-art studies on data-driven delay distributions.

Literature	Data	Methodologies or systems
[53]	Harz Region in the center of Germany:598 stations, 92 vehicles, and 31 lines	Data-based methods,GM
[54]	Trains of IC1900, IC2100 and IC2400 of Norwegian: 594, 340 and 327 records respectively during 2001 and 2003	Statistical analysis
[55]	32.4 million train movements for all trains in Sweden during the year of 2015	Statistical methods
[23]	Delay trains which have 10,000 weather-related minutes from the UK rail networks on June 28, 2012	Case study
[27]	Delays records for freight trains in eight train districts in the western USA from January 2001 to August 2006	Statistical methods
[56]	Over 6,000 train departures from metropolitan commuter rail-based upon the Dublin Area Rapid Transit rail system	Statistical analysis
[57]	96, 319 and 92 records respectively of stations Høn, Oslo, and Sandvika in Norway railway from June 01, 2005 to May 31, 2006	Statistical analysis
[58]	Data from 24 routes across the Railtrack network in the UK between April 2001 and June 2002	Statistical analysis
[59]	Data from the Taiwan HSR	Linear regression
[29]	Over 1,200 train operation records from February 24, 2015, to November 30, 2015, from Wuhan-Guangzhou HSR in China	Statistical analysis
[60]	More than 86,000 trains from January 2013 to May 2014 from Wuhan–Guangzhou HSR	Statistical analysis
[24]	Train numbers, arrival times, departure times at stations, track and other related information	Visualization methods
[17]	3-year rolling window for around 1,000 stations and 10,000 trains per day in SBB	Mathematical methods; Visualization methods
[61]	Data from TOZAI Line in Japan	Visualization methods; Simulation algorithm
[62]	Fragility parameters in 50 years	Fault-tree analysis methods
[63]	Data of train D301 and train D3115 on 20:30, July 23, 2011	Fault-tree analysis methods; Quantitative analysis
[64]	Data from the Beijing URT Line 8 Olympic Center Station	Fault tree analysis, AHP evaluation model
[65]	7 or 14 days historical readings in USA Class I railroad in 2011	Correlation analysis, Causal analysis, ML methods
[66]	More than 1000 trains and several checkpoints in more than 6 months in Italy	Kernel methods, Extreme learning machine
[67]	More than 360000 records from TRA from April 04, 2011 to May 31, 2012	Decision tree, Topology analysis
[68]	27 hourly trains between Urayasu Station and Kayabacho Station on weekdays in the most congested morning rush hours in June 2008	Visualization methods
[19]	Passenger trains at the LN station during the entire day for the week of June 16-20, 2003 in Swiss Federal Railways	Visualization methods, Statistical methods
[69]	The Kystbanen (coastline), north Copenhagen, Denmark from April to December 2014	K-MEANS clustering
[70]	Data corresponding to the regional railway network in Asturias	Statistical methods
[71]	More than 1000 trains and several checkpoints in more than 6 months in Italy	Deep extreme learning machine
[21]	Data from the line Copenhagen-Roskilde in Rail Net Denmark from 2014	Statistical analysis
[50]	Approximately 1,400 trains operating daily on Rail Net Denmark's network from January 2009 to March 2010	Percentile approach
[72]	Data from Sweden to Copenhagen Central Station in February 2012	Statistical analysis
[73]	18 simulation generated data from Rotterdam C to Den Haag	Stochastic simulation, regression analysis
[74]	1846 trains in Eindhoven during one week in September 1997	Statistical analysis
[75]	Nearly 10000 trains during September 1999 at Hague HS station	Statistical analysis
[76]	Two parts of the Dutch railway network between 1997 and 1998	Queueing network model
[77]	Over 200,000 departures records from 23 major stations for the period September 2005 to October 2006 on the British railway	Super statistical model, Q-exponential function
[78]	Around 10000 trains during September 1999 in the Hague HS station	Statistical analysis
[79]	Nearly 10000 trains during September 1999 at Hague HS station	Statistical analysis
[80]	Data from Basel in Swiss railway network	EM-algorithm, Iteratively optimize
[41]	Data from the corridor Rotterdam-The Hague of Dutch railway during February 2009	Data mining, Statistical analysis
[81]	29,662 HSR train records of Wuhan-Guangzhou HSR from February 24, 2015, to November 30, 2015.	Distribution models
[82]	Train operation records of Wuhan-Guangzhou HSR from February 2015 to November 2015	Distribution models
[83]	"Kystbane", the coastal railway running north from Copenhagen, from the period September through November 2014	Distribution models
[84]	Data from Dutch train describer during March 2000 between Zwijndrecht and Rotterdam Centraal	Statistical analysis, Linear regression analysis, Robust regression
[85]	Data in the entire Dutch railway network from January 1, 2011, to June 30, 2013	Probabilistic model
[86]	72 trains in Germany Railway network with 71 stations.	ML methods
[87]	602 train delay events from January 1, 2010, to June 30, 2016, of Taiwan High-speed Rail	Decision tree, SVM
[98]	High-speed trains' records from April 21, 2014, to November 21, 2016, of HSR in Guangzhou Railway	SVM

time adjustments that may be experienced during their operations.

a: SM

Results supported the strong correlation between arrival delays and dwell times, focusing on a statistical analysis of running times between stations to make predictions of the delay propagation in a railway system [84]. Phase-type distributions that can derive secondary delay distributions from primary delay distributions have been proposed [91]. Yuan and Hansen [48] presented an analytical stochastic model for estimating the propagation of train delays, and the key issue is how to estimate the convolution of individual independent distributions. Validation results reveal that the proposed analytical stochastic model effectively estimates the propagation of train delays and consequently, the punctuality of train arrivals, departures, and knock-on delays of trains. Correlation statistics are used to mine delay dependencies in large-scale real-world delay data obtained from the SBB network during two months of the timetable [49]. However, without any assumption on the statistical distribution of data, algorithms that efficiently find systematic dependencies in large-scale railway delay data are proposed.

Regression models obtained from delay distributions can serve as prediction models [54], [73]. Therefore, advanced minimum running time estimations may be used as a piecewise linear function that consists of the maximum number of regression lines for small delays and a small percentile for large delays. Passenger boarding and alighting events contribute to the dwell time prediction of trains [92], [93]. Murali *et al.* present a delay regression-based estimation technique that models delay as a function of the mix of trains and the network topology [94]. Guo *et al.* [95] consider the train operation as a sequence of discrete events and apply a linear regression model when modeling the delay prediction. The delay interpretation and dependencies are learned from historical data obtained from five stations on the Beijing–Shanghai HSR. A combination of linear regression and combinatorial model is generated from the online train delay monitoring data and is tested on the basis of a regional corridor from Lucerne, and resulted in low prediction error, although capacity constraints within stations are not considered [96].

Most recently, Kecman and Goverde [97] presented models that were developed by collecting all running and dwell time data from the training set and creating a separate predictive model to estimate each type of process time. This model confirms that regardless of departure delays, the majority of running times seem to be weakly affected by peak hours and do not have a remarkable daily variation. Li *et al.* [98] developed parametric and non-parametric regression models to estimate dwell times at shortstops for real-time scheduling, which is driven by train detection data from the Netherlands. Peak-hour dwell times are estimated using a linear regression model of train length and dwell times at previous and preceding trains. The off-peak-hour dwell times are estimated using a non-parametric regression model, particularly the k-nearest neighbor model.

A visualization and analytic system that can perform delay forecasting for the passenger information control system has been used since July 2003 [99]. This system generates delay status information that can show delay propagation.

b: GM

Difficulty in delay prediction is mainly due to unpredictable factors that affect train event times, and the key issue is to model uncertainties during train status transition. To this end, computation theories such as graph theory, Markov chain, fuzzy network, and Bayesian network are employed.

A data-mining approach is used to analyze rail transport delay chains with data from passenger train traffic on the Finnish rail network; however, data from the train running process are limited to one month [22]. Also, event graphs are used to forecast running, arrival times, dwell times, and headways [47], [84]. Kecman and Goverde [100] employ a timed event graph with dynamic arc weights to set up a microscopic model for the accurate prediction of train event times. Through this model, train interactions are modeled with high accuracy by involving operational constraints and following the actual headway time between adjacent trains.

A laboratory version of the real-time dispatching system called ROMA was developed and tested on an offline dataset to automatically recover disturbances and proactively detect each time interval [31], [101], [102]. The alternative graph is a suitable model for the job shop problem and can easily model several real-world constraints. The main value of the alternative graph is the detailed representation of the network topology at the level of railway signal aspects and operational rules, which can provide fruitful data and rules for other modules.

Barta *et al.* [103] developed a Markov chain model to evaluate the evolution of freight train delays at their successive terminals and classify terminals in terms of the roles of the trains. Şahin [26] established a Markov chain model to illustrate delay propagation and recovery using the observed historical data collected from a single-track line of the Turkish State railways. When the data-driven status transition matrix is available, predicting train states at certain event time steps and estimating steady-state delay probabilities will be possible. However, data used for modeling in this paper were 6-h and 18-station train-graphs of seven days, and only six delay cause classes that distinguish delay states are used. Based on the assumption that the probability of a state change depends on the moment of transition, train delay predictions are modeled by using a non-stationary Markov chain [104].

A fuzzy Petri net (FPN) model in which expert knowledge is used to define fuzzy sets and rules, transforming expertise into a model to calculate train delays, is proposed to estimate train delays [28], [105]. The proposed dispatching rules, which is empirically verified under different circumstances, can serve as training documents of the central training center and can be a basis of the decision-making system for dispatchers by interviewing dispatch experts with more than 10 years of experience in the central train control center of Taiwan railways [106]. In the triangular fuzzy number workflow nets of high-speed train running state models, the fuzzy time for train activities are generated on the basis of data for June 21–24, 2012 at five stations between Beijing–South, and Dezhou–East of the Beijing–Shanghai HSR [107]. The probability of different deviation times is obtained by initially using least-squares linear regression.

The transition matrix is generated from actual records of train movements when applying the Markov chain to model the delay propagation [26]. The Bayesian networks can timely update train running status based on new operation data. Zilko *et al.* [85] first attempted to apply the NPBN, which represents the joint distribution among variables that describe the nature of the disruption to predict the disruption length to the Dutch Operational Rail Control Centre. Later, they extended a new model with copula Bayesian networks, which consider the factors that influence the length of disruptions and models the dependence between them [108]. We proposed a hybrid Bayesian network model to predict HSR delays using the train operation records of Wuhan–Guangzhou HSR. The proposed model on overage can achieve over 80% accuracy in predictions within a 60-min horizon [109]. Of course, the joint method with Bayesian Reasoning and Markov model can be used to predict the delay state in different station [110], [111]

c: ML

Kecman and Goverde [97] proposed a statistical learning method that combines SM and ML methods. The modeling is divided into three steps, namely, least-trimmed squares robust linear regression, regression trees, and random forests. The complementary advantages of these three types of models enabled the statistical learning methods to outperform other models. A supervised decision tree method that follows the ML and data mining techniques is designed to estimate the key factors in knock-on delays [67]. The proposed model can be used in predicting lengths of railway disruptions with high accuracy using delay history data. A hybrid approach that combined decision tree and random forest regression is also used to predict the running time, dwell time, train delay and penalty costs, which merges the data-driven model and experience-based models approaches [112].

ANN, as a basic ML method, learn from historical data to make predictions about future [113]. Peters *et al.* [114] applied ANN to process existing delays abstracted from known operation data to generate delay predictions for depending trains shortly; this method performs well when predicting future (secondary) delays based on existing (primary) delays, and it outperforms the traditional rule-based method. Yaghini *et al.* [115] also presented an ANN model with high accuracy to predict the delay of passenger trains in Iran; the comparison of the proposed ANN, decision trees, and multinomial logistic regression models confirm that the ANN model has high accuracy, low training time, and remarkable solution qualities.

Also, support vector regression (SVR) in passenger and freight train arrival delays prediction is implemented in [116], [117]. The comparison between the proposed SVR model and the ANN model shows that the SVR outperforms ANN because it achieves higher average R^2 than ANN on the test data. The models, based on the least-squares method, SVM, and least square SVM were trained and tested by using the field data collected in Wuhan–Guangzhou HSR and were proposed to predict train positions. These methods enabled the prediction of the HSR train position and the running time [118].

Most recently, the shallow and deep extreme learning machine (DELM) was proposed, along with the rapid development of big data technologies. Oneto *et al.* [20], [66] presented a data-driven TDPS for a large-scale railway network to provide useful information to RTC processes by using state-of-the-art tools and techniques; this system can extract information from a large amount of historical train movement data using the most recent big data technologies, learning algorithms, and statistical tools. The described approach and prediction system have been validated on the basis of real historical data in six months. The results show that the DELM outperforms the current technique, which is mainly based on the event graph proposed by Kecman and Goverde [100]. Using the findings of Oneto *et al.* [20] as a basis, Oneto *et al.* [71] developed a data-driven dynamic train delay prediction system (DTDPS), which can integrate heterogeneous data sources to deal with varying dynamic systems using DELM. Exploiting state-of-the-art tools and techniques, this system is entirely data-driven and does not require any prior information about the railway network.

2) DELAY RECOVERY

a: SM

The majority of recent studies have focused on the area of delay recovery models and algorithms. Three classes of real-time schedule recovery, namely, vehicle rescheduling for road-based services, train-based rescheduling, and airline schedule recovery problems, are reviewed in [119]. Another overview of recovery models and algorithms for real-time railway disturbance and disruption management that mainly summarized methods on real-time TTR of the rolling stock and crew duties is presented in [7].

Naohiko *et al.* [120] briefly discussed the recovery measure of disruption in train operations in the Tokyo metropolitan area and apply three kinds of data, namely, train accident, train operation record, and delay certificate data. Interviews with 19 transportation staff of 9 companies with regard to rescheduling methods at the time of the accident with casualty provided recovery effects of the various strategies conducted by dispatchers. Although this study only proposed an interview result and statistics on delay recovery, it presented a data-driven method of the measurement of delay recovery.

Liebchen *et al.* [121] introduced recoverable robustness into train delay recovery to jointly optimize the plan and strategy for limited recovery. Based on the assumption of uncertainty at the running and dwell times of trains, different recovery possibilities can be obtained from the historical data. Recoverable robustness integrates timetabling and the so-called disturbance management under different scenarios with various recovery possibilities.

b: GM

The alternative graph can be generated after all the necessary information has been elaborated by the loaded information, and the disruption recovery module of the ROMA checks if block sections in the network are unavailable and automatically recovers disturbances [31], [101], [102]. Cadarso *et al.* [122], [123] proposed a two-step approach that combined passenger demand pattern anticipated by a discrete choice model and an integrated optimization model for the timetable and rolling stocks to deal with recovery disruptions in large-scale rapid transit networks. The data-driven multinomial logit model was computed and validated by the Spanish rail operator RENFE based on passenger counts, inquiries, and historical data fittings.

Khadilkar [25] proposed a data-enabled stochastic model for evaluating the robustness of timetables by considering delay prediction and recovery. Regarding the time supplements, the running time between two stations is frequently used to absorb previous delays, and the delay recovery effectiveness is statistically estimated based on the empirical data. The average recovery rate of 0.13 min/km was used for the delay recovery ability obtained from more than 38,000 train arrival/departure records from the Indian Railway network. However, only the empirical data for 15 days were available for the study. Such a constant average recovery rate can hardly reflect the actual recovery potentials of different sections and stations.

c: ML

Recently, Wen *et al.* [124] presented two DDMs, namely, multiple linear regression models and random forest regression model, to address the problem of predicting delay recovery of HSR trains due to primary delays. Models were trained and tested using the 10-month train operation records from the Wuhan–Guangzhou HSR line in China. The researchers examined the relationships between train delay recovery (dependent variable) and four independent variables, namely, primary delay duration, total scheduled dwell time for all downstream stations, total supplements in all downstream sections, and a binary variable. The validation tests indicate that both models can achieve considerable performance, whereas the random forest model outperforms the multiple linear regression models in delay recovery prediction accuracy. Moreover, the proposed random forest regression is superior to the extreme learning machine (ELM) and stochastic gradient descent methods [125] and [126] under the same explanatory variables and dataset.

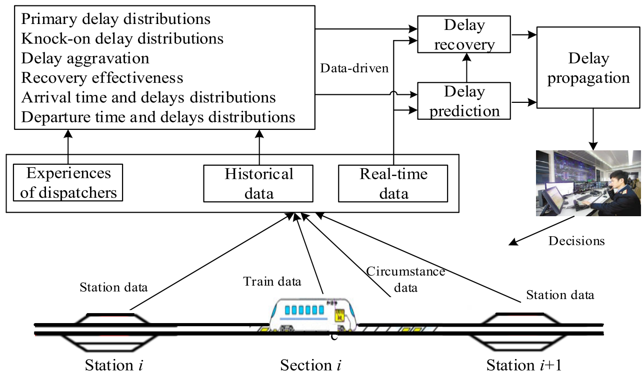

FIGURE 6. **Roadmap of data-driven delay propagation.**

3) STATE-OF-THE-ART ON DELAY PROPAGATION

Existing studies on delay propagation show that data-driven delay prediction and recovery are universally concerned with theory and practice. Table 4 shows a summary of state-of-the-art studies on data-driven delay propagation.

Figure 6 depicts the research roadmap of data-driven delay propagation. Dispatchers need a continuous estimation of succeeding train status, including the arrival and departure time at stations, running time in sections, and delays at stations and sections. The primary and knock-on delay models should be set up, and how delays are recovered should be revealed based on delay distributions, delay and aggravation, and recovery effectiveness obtained from experiences and historical data. Attention should be paid to the ML/DL in delay propagation estimation and evaluation without any assumption on statistical data distributions to reveal the mechanism of delay development.

The reviewed studies have four shortages regarding delay propagation:

1) Researchers tend to study the issues of delay propagation and recovery with GM methods, such as Petri Net with Fuzzy Logic, which rely too much on the prior dispatching knowledge.
2) Studies involving delay propagation due to different causes and delay durations are lacking. It is necessary to study the influence of delays, including the affected trains and time intervals.
3) The models of primary delays and knock-on delays should be set up respectively, and how delays are recovered should be revealed lying on delay distributions, delay and aggravation, and recovery effectiveness that obtained from the experiences and historical data.
4) Researchers mainly study the delay propagation for a specific railway line instead of a complex network. The interaction between the delay propagation in the horizon direction and the vertical direction need to be studied in-depth, and how a delay propagates on a railway network should be more significant.

The ML/DL needs to be paid more attention to delay propagation estimation and evaluation, without any assumption on

TABLE 4. Summary of the state-of-the-art studies on data-driven delay propagation.

Literature	Data	Methodologies or systems
[32]	Trains locally rerouted to bypass the disruption, canceled services in the Den Bosch, Nijmegen, Arnhem, and Utrecht stations	ROMA dispatching system
[90]	30 trains in 14 stations	Fuzzy expert systems
[91]	Actual timetable in a part of the Netherlands intercity railway network with four lines	EMPHT program
[92]	Passenger boarding and alighting data from seven busy stations in the Netherlands	Statistical methods
[93]	Broader data from door sensors, passenger counters, and train event recorders	Statistical methods
[94]	Trains' state data from Downtown Los Angeles-Inland Empire Trade Corridor in the USA	Simulation-based technique
[95]	Historical data from 5 stations on the Beijing-Shanghai HSR	Linear regression model
[96]	Train delay monitoring data of Swiss Railways	Linear regression
[97]	Running times of nine train lines over 143 blocks and the dwell times of 9 train lines in 19 stations in 82 days from the areas Rotterdam and the Hague	Statistical learning method
[98]	A train detection dataset of Dutch railway line from September 1, to November 30, 2012	Parametric regression, Non-parametric regression model
[99]	Train tracking information of Tokaido-Sanyo Shinkansen	Delay forecasting system
[100]	Historical track occupation data of a busy corridor in the Netherlands	Statistical model
[31]	Train timetables in 2007 of the route Utrecht-Den Bosch	Real-time dispatching system
[101]	Secondary delays based on the Schiphol dispatching area	Branch and bound algorithm
[102]	Records of the Dutch signaling system NS54	Heuristic algorithm
[103]	Historical data of the Hupac transportation network from February to June 2011	Markov chain model
[26]	Data of the TCDD during 14-20 July of 2002	Markov chain model
[104]	Traffic realization data between Beijing and Shanghai from December 2013 to March 2014	Non-stationary Markov chain model
[28]	Track occupation data and practical train timetable from the year 2012 of the Belgrade railway node	Fuzzy Petri net model
[48]	Track occupation data and train timetable of the Dutch railway station The Hague Holland Spoor.	Analytical stochastic model
[49]	Several important operating points of the SBB network during two months of 2008	Correlation statistics
[22]	Data from passenger train traffic on the Finnish rail network during September 2009	Data mining
[105]	Passenger loads, fluctuation of a passenger load and bus encounter probability in four terminals.	Fuzzy Petri net model
[106]	Train dispatching data of a line section of Taiwan's network	Fuzzy Petri net
[107]	Data at five stations between BeijingSouth and DezhouEast of Beijing-Shanghai HSR during June 21-24, 2012	Triangular fuzzy number workflow nets model
[108]	Track circuit disruptions in the Dutch railway network	Copula Bayesian Networks model
[109]	378510 arrival and departure events from February. 2015 to November 2015 on Wuhan-Guangzhou HSR	Hybrid Bayesian Network Model
[110, 111]	a very small section of the Great Western Rail line in UK	Markov model
[112]	12 months (the whole 2016 solar year) of train movements of one big Italian Region (Liguria)	Decision tree and random forest regression
[113]	the data of Thailand for six months from June 1, 2013 to November 30, 2013	KNN algorithm
[114]	Operation data in the network	Neural networks
[115]	Data of passenger train delays from 2005 to 2009: 18 174 hours per year and 30 minutes for each train	Artificial neural network model
[116]	Train arrival delay data of different routes of Serbian Railways	Support vector regression
[117]	The CSX Transportation data from December 1, 2014 through January 31,2017	Support vector regression
[118]	Data from February. 2015 to November 2015 on Wuhan-Guangzhou HSR	LSM、SVM、LSSVM
[20]	Historical train movements data of the Italian railway network	Data-driven dynamic train delay prediction system
[120]	Actual train operation data from 9 railway companies in 2012	Data-driven method of delay recovery measuring
[121]	Recover time of original method and recovery robust approach in Palermo Centrale station.	Recoverable robustness methods
[122]	Passengers' and operators' costs based on realistic cases in Madrid for 2008	Two-step approach
[123]	Passengers' and operators' costs based on realistic cases in Madrid for 2008	Two-step approach
[25]	Empirical data for 15 days of operations of the Mumbai-New Delhi railway	Stochastic delay propagation model
[124]	Train operation records from the Wuhan-Guangzhou HSR line in 10 months	Multiple linear regression models and random forest regression model

statistical distributions of data, revealing the mechanism of delay development.

C. DATA-DRIVEN TIMETABLE RESCHEDULING: LITERATURE

1) CONFLICT DETECTION AND RESOLUTION

As reviewed in [127], over four decades have passed since the conflict management problem in train operations around the world was first studied, and several systems and the CDR module have been developed. Existing studies on CDR mainly apply CI methods, especially knowledge-based methods and graph theories as well as ML, which are effective methods for dealing with CDR using train operation data.

a: SM

Chen and Harker [128] firstly model the probability of a train's historical dispatching data, delaying a particular train due to actual conflicts, and the conflict delay between two trains is based on this probability and the probability of the two trains interfering with each other. The latter probability is dependent on the outcome of prior conflicts in the schedule and unforeseen events. Train operation conflict number is usually used to study the characters of delays and conflict severity between trains; for example, the delay risk and reliability of train arrival times [129], [130]. The number of conflicts has been considered as one of the most important indexes to measure the severity of delays.

b: GM

Hansen *et al.* [47] presented a delay propagation model in which train path conflicts and dispatching decisions are considered and estimated the parameters through the offline statistical analysis of historical train operation data. Medeossi *et al.* [131] defined conflicts regarding probability by calibrating the motion equation with the train tracking data obtained from GPS or train event recorders, using performance parameters and calibrated motion equations with initial delay and stop time distributions from building stochastic blocking times. A set of tools for CDR were proposed by the Multilevel Advanced Railways Conflict Resolution and Operation (MARCO) project, which pioneered the development of tools, algorithms, and technologies for CDR [132]. Designer of Network Schedules was developed to design a conflict-free timetable in Dutch [133]. The COMBINE and COMBINE2 projects aimed to develop a traffic management system (TMS) based on MARCO [38], [134]. The dispatching support system, ROMA, which aims to compute flexible conflict-free timetables, detect and resolve conflicts, and terminate delay propagation, was proposed in [135], [136]. Another set of tools called TNV was developed, which mainly consisted of TNV-Prepare, TNV-Conflict, and TNV-Statistics [137]. Subsequently, the the train observation and tracking system (TROTS) was developed to use operation data from Dutch train describers, thus serving as a dispatching support system [138].

Knowledge-based DDM systems that rely on artificial intelligence were utilized to deal with CD and CR during the 1990s. The expert system for real-time train dispatching, in which computer-aided technologies are employed to process the human expertise and train operation data, is used in detecting and resolving train conflicts [139]. In this system, the CD is triggered by the automatic train tracking system, and CR is conducted based on a highly detailed data modeling of train operation constraints. Subsequently, the knowledge extracted from human experts is used to search for a reasonable conflict resolution [140]. Similarly, the work experiences of dispatchers for more than 10 years are used as the basic rules for CDR in the knowledge-based system [106].

Furthermore, the fuzzy network theory is widely used to solve CDR problems. Fay [141] proposed a dispatching support system with expert knowledge in fuzzy rules of "IF-THEN" type and used an FPN notation to model the rule-based expert knowledge in a decision system. The modeled expert knowledge was used as the rule for the "selection of feasible actions" for conflict classification and resolution, which would affect the development of conflicts directly. Then, Zhuang *et al.* [142] applied a timed Petri net to model the HSR train timetable to study conflict prediction using the fuzzification of time intervals in a train timetable based on historical statistics. Based on the temporal fuzzy reasoning method, a new conflict prediction method is proposed, and the results under two scenarios of HSR in China prove that conflict prediction after the fuzzy processing of the time intervals of a train timetable is reliable and practical. Conflicts between successive stations and within stations are identified and solved with the fuzzy logic system, where expertise is used to establish fuzzy rules and adjust train dwell times [143]. The fuzzy rules from this knowledge after fuzzification could express their actual meaning effectively.

As reviewed in the part of delay prediction, pre-loaded data and accurately updated data are used by ROMA in predicting delay and then identifying conflict; the conflict identification can usually be the direct result of delay prediction. In an alternative graph, a fixed arc is a fixed precedence relation, an alternative arc represents an alternative precedence relation, and the weights of both kinds of arcs that are calculated by historical data are considered the arc lengths [144], [145]. After loading all data and determining all arc weights, offline conflicts can be detected using a topological visit of the alternative graph, and alternative arcs are used to avoid conflicts between trains [31].

TNV systems maintain a real-time record of train description steps and received events from the safety and signaling systems, with the precision of a second [16]. The TNV-Prepare tool generates TNV-tables that provide various opportunities to analyze railway operations, including capacity analysis, punctuality analysis, and assessment of stochastic railway processes. Subsequently, the TNV-Conflict tool was developed to identify all signaled route conflicts automatically, including critical sections and conflicting trains [137]. Later, the TNV-Statistics tool was developed and added to TNV-Conflict to determine chains of route conflicts with associated secondary delays and rank signals according to the number of conflicts, time loss, or delay jump [36]. The TNV system was recently replaced by TROTS, a process mining tool based on event data records from the Dutch train describer system, which aims to minimize train disruptions and improve operation safety in railway systems [39].

c: ML

Most recently, artificial intelligent DDMs were proposed to deal with CDR problems. The D-Agent method was developed to study CDR problems and support dispatchers in making decisions on station operation [146]. The D-Agent was designed to learn from its history in applying different decisions experimentally and evaluating skills by the preference weights of alternative solutions in a particular task. It is composed of five basic modules: local database, knowledge base, skill base, reasoning mechanism, and communication interfaces. Then, Zhu and De Pedro [147] proposed an approach to traffic state prediction and conflict detection that is based on proper state transition maps and corresponding relation matrices (anomaly analysis) to study the CD issue; the researchers used the corresponding state domain tables to maintain empirical data-driven traffic state sequences, which mainly concern infrastructure status and train movement information expressed as segment and route state vectors. The representative (statistical) state transition maps integrate timetable requirements to predict concrete traffic trends in a short period and detect abnormal states and irregular times. Then, conflict detection is conducted through the state transition under the restrictions of train operation principles and operational limitations.

2) BUFFER TIME ALLOCATION

a: SM

After analyzing historical data and distributing the buffer times in a complex and busy junction with minimum delay propagation, Yuan and Hansen [48], [148] concluded that as buffer times between trains decrease, knock-on delays increase exponentially; this condition confirms that the BTA is necessary to reduce the behavioral response and waste of resources. To investigate the quality of timetable supplement allocation and assess whether the timetable supplement in existing timetables fits the actual need and is properly used, Fabrizio *et al.* [21] presented a statistical approach to analyzing the historical data of train timekeeping in Denmark; their study shows that actual supplement times can be detected in a train path using historical data.

To measure the effectiveness of buffer times, weighted average distance (WAD), and buffer index (BI) were proposed. Vormans [149] defined WAD as the weighted average distance of supplements from the starting point of the train line, which can be calculated using the historical trips of trains. Based on the analysis of historical data in [149], strategies of buffer time distributions were proposed; namely, the uniform distribution of margins, shifting margins toward the beginning or end, placing margins at or near strategic locations, and locating buffer times where disturbance occurs most frequently. WAD aims to describe how supplements are distributed along the journey and attempt to optimize this process, using both analytical and numerical methods. Similarly, WADs are applied in the approach that combines linear programming (LP) with stochastic programming and robust optimization techniques to improve the robustness of a timetable [150]. The strategy of placing margins at critical points was developed by Andersson *et al.* [151]. Kroon *et al.* [152] introduced a stochastic optimization model that can be used for modifying a given cyclic timetable in which WAD is used as a measure. The authors concluded that with the optimal allocation of different amounts of total slack, the distribution favors early buffer supplement (low WAD) when a small total buffer supplement is available. Recently, Palmqvist *et al.* [153] employed the analytical method to study the problem of BTA strategies that depend on the effectiveness of margins on the punctuality of passenger trains. Results imply that every additional percentage point of margins improves punctuality by approximately 0.1%, and approximately the same for every percent increase in the WAD of margins. The BI is calculated from a delay and a buffer time for each train and station and represents a characteristic of the delay due to knock-on delays [61]. By calculating the BI for all trains and stations, the existence of a train whose BI is larger than those of the surrounding trains at a station can be determined, and a delay is likely to propagate rapidly to the succeeding trains from that train at the station.

To increase the robustness of a timetable against delay propagation, the scheduled running time in sections, and the dwell time at stations are often larger than the minimum required running and dwell times [154]. However, allocating excessive time supplements can extend the travel times for trains and increase infrastructure capacity loss [1]. Therefore, the BTA should be addressed during timetable scheduling and rescheduling with consideration for delay occurrence and recovery factors. According to the UIC CODE 451-1 OR published by the International Union of Railways, regular running time supplements are added to every train path in the timetable in three ways: based on the distance driven (min/km), travel time (%), and fixed supplements per station or junction (min) [155]. Supplements vary in different countries due to local circumstances. For instance, running time supplements are approximately 7% for all trains in the Netherlands and passenger trains in Switzerland compared with 11% for freight trains in Switzerland.

b: GM

Dispatching decisions partly focus on allocating a sufficient amount of time supplements to rail operations on the network [156] to compensate for stochastic arrival and departure delays of trains [157]. Goverde and Hansen emphasized that time allowance (buffer times) is a significant

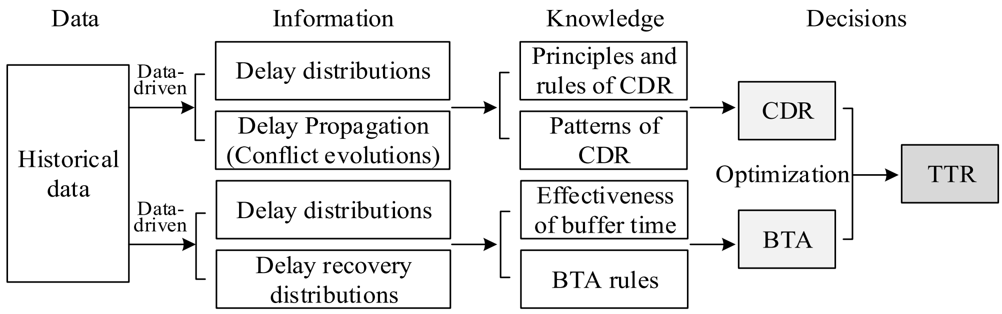

FIGURE 7. A research framework of data-driven timetable rescheduling.

indicator of timetable stability, that is, the effectiveness of avoiding or reducing delay propagation to another train [154]. They presented the recommended BTA principles in German railways and Netherland railways that are set as the basis of their operation experiences. Meanwhile, in the UK, the runtime and dwell time allowances (supplements) are not explicitly defined but are optimized according to the past performance obtained from historical operation data on the particular railway section [158]. The BTA problem is modeled as a knapsack problem, and Jovanović *et al.* [41] inferred that the recent increase in the availability of historical traffic data could be exploited to prioritize candidate places in the schedule for buffer time assignment and the DDMs can be applied for BTA.

Vansteenwegen and Oudheusden [159] first investigated the desired buffer times in a timetable and then established an LP problem that penalizes the positive and negative deviations from the desired values. The ideal buffer times are calculated to safeguard the connections and transfers between trains. These buffer times are based on the delay distributions of arriving trains and on the weighting of different types of waiting times obtained from the Belgian train operation data.

c: ML

Huang *et al.* [160] established a data-driven BTA model based on the Wuhan–Guangzhou high-speed railway. A ML model named ridge regression model is proposed to explain delay recovery time regarding buffer times at stations, buffer times in sections, and the severity of the primary delays. Based on the utilization of buffer time, the model redistributes buffer time, which provides a new research method for BTA. The proposed ML model has aroused a new method to incorporate real-world timetables performance indices such as the buffer time utilization ratio and delay probability derived from historical records using ML methods.

3) STATE-OF-THE-ART ON TIMETABLE RESCHEDULING

TTR is the carrier of decisions by which dispatchers regulate the train operation constantly in their domain. The important issues on TTR, CDR, and BTA have received considerable attention and seem to be promising research fields. Several tree-based or knowledge-based rules are obtained from data to determine the optimal input-output patterns and make better real-time decisions during operation disturbances in HSRs, timetable design, and optimization [161]. Table 5 presents a summary of the state-of-the-art studies on data-driven timetable rescheduling.

Therefore, integrating methods combining both optimization and DDMs for TTR are necessary for real-time train control. The research roadmap of data-driven TTR can be depicted in Figure 7.

Knowledge-based models, alternative graphs, and fuzzy logic are the most popular DDMs that have been applied in CDR. The key challenges of these approaches are mining conflict identification principles, obtaining conflict resolution rules, and dependence on historical data. The review of the studies listed above reveals that the BTA mainly relies on measuring the effectiveness of buffer times based on historical data, such as WAD, and searching for an approach to optimize the allocation of buffer times, combining the effectiveness of buffer times on delays or disruptions.

The reviewed studies have four shortcomings concerning the data-driven timetable rescheduling:

(1) The rules of the evolution of train conflicts need to be studied in-depth, and the theories of intelligent CDR need to be developed.
(2) The issues need to be addressed concerning how a disturbance leads to conflict, how buffer time absorb delays, and how to resolve the challenges. The modeling of conflict chains has been proved to be a hard but significant problem.
(3) There is a lack of models that can incorporate real-world timetable performances indices such as different buffer time utilization rates and delay probabilities obtained from historical records. Since delay propagation and recovery problems are highly dependent on operational factors and conditions that are realized during train operations, in practice, the BTA should be carried out by considering characteristics of implemented timetables. The BTA scheme needs to obtain better recovery effectiveness against delays.
(4) Assessments of dispatching qualities of different strategies are lacking.

TABLE 5. Summary of the state-of-the-art studies on data-driven timetable rescheduling.

Literature	Data	Methodologies or systems
[128]	Arrival and departure records from a portion of single track from a major U.S. Class I railroad	Probability models
[129, 130]	Data from an 89km-length single-track rail corridor with 14 stations/sidings	Analytically based models
[131]	Train tracking data from approximately 100 trains on the Trieste–Udine rail line in Northeast Italy	Motion equations, Stochastic blocking times
[132]	Arrival and departure times of 300 trains passing through terminus at peak hours of Milan Metro	Conflict detection and resolution
[133]	Train timetable and railway infrastructure status data of the Dutch Railway	Decision support systems
[134]	Simulation data from the actual Dutch railway network connecting Antwerpen – Breda – Rotterdam – Vlissingen	Traffic management system
[135]	Real-time data and train characteristics of rail network between Leiden and Amsterdam.	Intelligent conflict detection and resolution system
[136]	140,000 respondents of the questionnaire survey of commuting traffic in Tokyo Metropolitan area in 2005	Time-space network
[137]	Chronological infrastructure and train description messages of the railway line from Rotterdam to Dordrecht	TNV-Conflict
[138]	Chronological infrastructure and train description messages of the railway line from Rotterdam to Dordrecht	Colored Petri net
[139]	Passenger trains with different speeds (90 km/h up to 200 km/h) in North-West German	Analytical conflict detection, Decision tree
[140]	Train operation data of 102 stations and 350 trains of the Taiwan Railway network	Job-shop scheduling
[141]	Data of the railway traffic fuzzy traffic control operation and rule-based operation results	Fuzzy Petri Net
[142]	6 stations and 15 HSR train trains of the Beijing South–Jinan West	Timed Petri net, Temporal fuzzy reasoning
[143]	The actual timetable of south-east Asian single-track bi-directional railway	Fuzzy inference
[144]	Arrival and departure data recorded of 100 timetable perturbation instances by ProRail at Utrecht Central in April 2008	Alternative graph, Space-time diagram
[145]	Actual timetable at Schiphol bottleneck in 2007	Traffic management system
[16]	The actual speed, arrival and departure times of the Dutch train	TNV-tables data analysis
[36]	Real-time data on a busy railway corridor in The Netherlands	TNV-Statistics, Conflict trees
[146]	Detailed infrastructure data, planned and actual train sequence, route table, arrival and departure time of railway network	D-Agent simulation, MILP formulations, Decision support system
[147]	Data of the train actual train movement information, track occupation, original infrastructure states of a station SA with 16 segments	State transition maps
[148]	Primary delays, knock-on delays, and buffer times between scheduled trains at railway bottlenecks	Analytical approach
[149]	Arrival times of each train in the 800-line-from Haarlem to Maastricht and the 900-line-from Haarlem to Heerlen	Analytical approach
[150]	Four single-line medium-size instances in the Italian railway	Stochastic programming Robust optimization
[151]	Empirical observations data of the Swedish timetable and the Swedish Southern mainline during 2011	Robustness measure analysis
[152]	500 realizations of trains on the corridor Haarlem–Maastricht/Heerlen under stochastic disturbances	Stochastic optimization model
[153]	Almost 46,000 distinct timetable versions and over 1.1 million departures in 2015 in Swedish railway network.	Margins assigning Strategies
[154]	Records of primary delays and the settling time absorbed.in timetabling	Classification method
[157]	Estimated waiting time, the occupation of different track sections and buffer time within the station of Den Hague HS	Queuing theory
[158]	67,000 train runs on approximate 4,500 km during 4.00pm-9.00pm in the timetable of 2001-2002 of the network of Hannover and Mannheim	Analytical approach, Railsys
[159]	Passenger flow and train running data in a small part of the Belgian railway network	Linear programming
[160]	Over 64,547 HSR train operation records from during 24 March 2015, to 10 November 2016, from Wuhan-Guangzhou HSR in China	Ridge regression model
[161]	Basic train operation data in THSR Company	Tree-based operation Linear programming

Considering these issues, ML and DL methods have advantages in learning principles and rules for CDR. These can provide more patterns of CDR schemes based on the ML and DL methods that can learn much from more cases. In this way, more detailed and specific solutions are expected and possible for usage in CDR. The BTA scheme must obtain better recovery effectiveness against delays. Given rich train operation records, models can be established from past performances to describe the effectiveness of buffer times rather than using indicators, such as WAD and BI. Models, such as regression models of BTA against delay recovery, can be used as input to BTA. Models that apply ML should also be considered to learn BTA rules from historical data and optimize BAT schemes automatically.

IV. REVIEW RESULTS AND FURTHER DISCUSSIONS

A. DEVELOPMENT OF DATA-DRIVEN TRAIN DISPATCHING THEORIES AND IMPLEMENTATION

High punctuality of trains is an important factor considered by railway companies. However, trains are influenced by bad weather, mechanical failure, and organizational strategies during operation, which could lead to disruptions. Accurately predicting train-delay propagation and the scope of influence can assist train dispatchers in estimating the train operation states accurately. The detailed assessment can provide a theoretical basis for rescheduling strategies, facilitate more scientific and reliable rescheduling decisions, and improve the theories of automatic train operations and the intelligent dispatching of railways.

According to section 3, we summarize the reviewed papers in Figure 8, which indicates that few ML methods and studies focus on TD. This summary illustrates the existence of a gap, which necessitates further research on the modeling of CDR and BTA with ML approaches. The distribution of reviewed articles by year is shown in Figure 9. The figure indicates that the application of DDMs in TD presents a generally increasing trend in the last two decades. ML methods have become more attractive in the last five years as big data has played a crucial role in DDMs, while many studies have focused on SM and GM from 2004 to 2013.

In summary, the DDTD theory was first proposed in the 1980s, and the knowledge-based expert systems for train-traffic control, named ESTRAC-I, II, and III were developed and implemented consequently in the 1980s and 1990s [90], [162]–[164], [167]. "IF-THEN" knowledge was used to represent the decision-making rules of dispatchers. Almost at the same time, the distributed approach to railway traffic control was described with the help of artificial intelligence, and a knowledge-based interactive train scheduling system-aiming at large-scale complex planning expert systems was developed [165], [166]. The development of ROMA in the 2000s has great contributions to the DDTD as reviewed above [135], [137]. The fuzzy logic and many other GM methods have been applied before 2014 [28], [106]. And the ML methods have been widely and rapidly applied in DDTD in the latest 5 years, based on RWTOD [20, 23, 127].

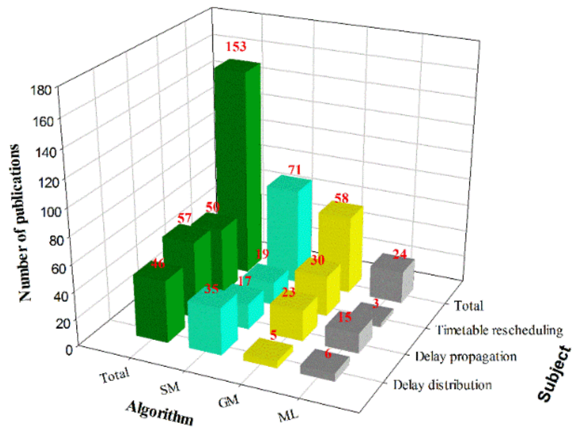

FIGURE 8. Number of publications reviewed on data-driven methods in TD.

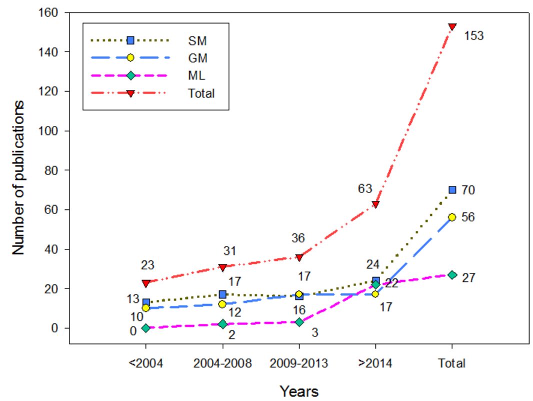

FIGURE 9. Trends of publications for the reviewed articles in each category.

In other words, TD is an issue that belongs to the problem of job-shop scheduling and system control [167]. Through data-driven methods, dispatching rules are discovered from the data for job-shop problems. The literature review shows that ML approaches have been widely applied over the last 20 years in the scheduling of manufacturing systems [168], [169]. This condition means that the ML approach based on preference learning can perform in uncovering train dispatching rules [170]. One of the most promising ML approaches is neural networks (NN) and variants, such as convolutional neural networks (CNNs) in image processing [171], deep belief networks (DBNs) in audio recognition [172], and recurrent neural networks (RNN) in sequence analysis [173]. RNN-based models have been successfully applied in travel time estimation in highways [174], [175] and air transport [176], but the applications in railway train delay/travel time prediction are limited. DL discovers the complex structure in large datasets by using the backpropagation algorithm to indicate how a machine should change its internal parameters used to compute the representation in each layer from the representation in the previous layer [177].

DL approaches have shown strong abilities in analyzing, evaluating, and predicting the performance of a complex system [178], [179]. To minimize the job scheduling time, a deep reinforcement learning method was proposed for studying multi-resource multi-machine job scheduling, revealing that deep reinforcement learning method has the potential to outperform traditional resource allocation algorithms in various complex environments [180].

B. FURTHER DISCUSSIONS: OPPORTUNITIES AND CHALLENGES

1) ML/DL DRIVEN TD

Based on RWTOD, with the advantages of ML/DL in data processing and modeling, there will be several potential applications in TD:

1) Integrated models of temporal, spatial, and cause-specific distribution models of delays must be established using detailed RWTOD during longer periods. More complex investigations regarding the delay distributions are required to determine the characteristics of delays. The modeling of the frequency and duration of the initial interruption and the subsequent knock-on delays are essential to assist the dispatchers making decisions. The compound distribution model, which consists of the occurrence time, sections, and stations of delays, are more valuable than the currently used models. The delay duration distribution model and the temporal and spatial distribution model of cross-line trains would be helpful to capture the basic delay features of the rail network. Using these models, dispatchers can obtain the real-time and future status of trains under certain operation circumstances. Clustering methods, such as k-means, can be used to classify delay categories, and the delay patterns can be derived from data and data-driven models. Delay distributions can also be used as input in data-driven simulation studies and distributional functions in predictive modeling for delay propagation.
2) DDMs can support dispatchers in having better predictions of delay propagation patterns and possible delays under specific situations to adjust train operations. The implementation effects of TDPS and DTDPS based on big-data technologies have shown good performance in terms of delay prediction [20], [71]. ML and DL methods can be used to model propagation patterns, in-train interactions, and the spatial and temporal relationship between adjacent trains. Exploring the delay rules and the propagation mechanisms and enhancing the delay-recovery capacity of the timetable are the critical issues required to be addressed to improve the efficiency and quality of train dispatching. Theories of train delay propagation and recovery using data-driven methods based on operational records are needed. Based on the RWTOD, studying delay propagation rules and evolution mechanisms, combined with delay and buffer time, on a network will continue to be crucial, especially for cross-line trains. After analyzing the mechanisms of delay propagation in the horizontal direction on the rail network, the influencing factors should be determined, including the number of affected trains and the event's duration. Various categorizations should be taken into account, and a quantitative prediction model of train delay influence indicators should be established separately. The delay propagation in horizontal direction model can be used for estimating the severity of delays and how they affect the operation of trains on the rail network. The model can also provide support in creating dispatching strategies.
3) DDMs can uncover more precise rules for CDR and BTA from RWTOD, including conflict identification principles, conflict resolution rules, and the effectiveness of buffer times. ML and DL models can be used to classify, model, forecast, and then optimize CDR and BTA on the basis of RWTOD. Moreover, rules for CDR and BTA are more likely to be obtained on the basis of RWTOD. For example, some conflict reasoning rules and conflict resolving rules can be mined by DL. Currently, the scheduling of a train timetable scarcely considers the impacts of the implementations, which brings adverse effects on the transport quality and capacity of the railway. Executing train timetable feedback optimization is a significant step in improving the quality of the timetable theoretically and practically. It is possible to reveal the evolutionary trend's structure concerning potential conflicts based on the train's operational data. When detecting a delay, a method to calculate the potential conflict situation is required. This situation can be considered as the optimized object in the data-driven CDR model, establishing the feedback optimization theory for timetable rescheduling using DDMs.
4) Delay recovery effectiveness measures can be obtained from RWTOD by CNN to update WAD. The BTA model based on deep reinforcement learning can be established to maximize the delay recovery capacity and increase the buffer time effectiveness. The delay recovery effectiveness measures can be obtained from RWTOD by CNN to update WAD. The BTA model based on DRL can be established to maximize the delay recovery capacity and increase the buffer time effectiveness. For different types of delays, based on RWTOD, modeling of temporal and spatial distributions of delay recovery due to buffer time need to be carried out first, and the characteristics of recover time under different BTA scheme should be investigated. DDMs will be used to calculate the buffer time distribution matrix and the delay recovery coefficient matrix. These matrices can be used to determine the timetable buffer time utilization efficiency and to identify significant trains, sections, and stations. Then, the delay-recovery chains should be established to derive the effectiveness of buffer times. Because of the close

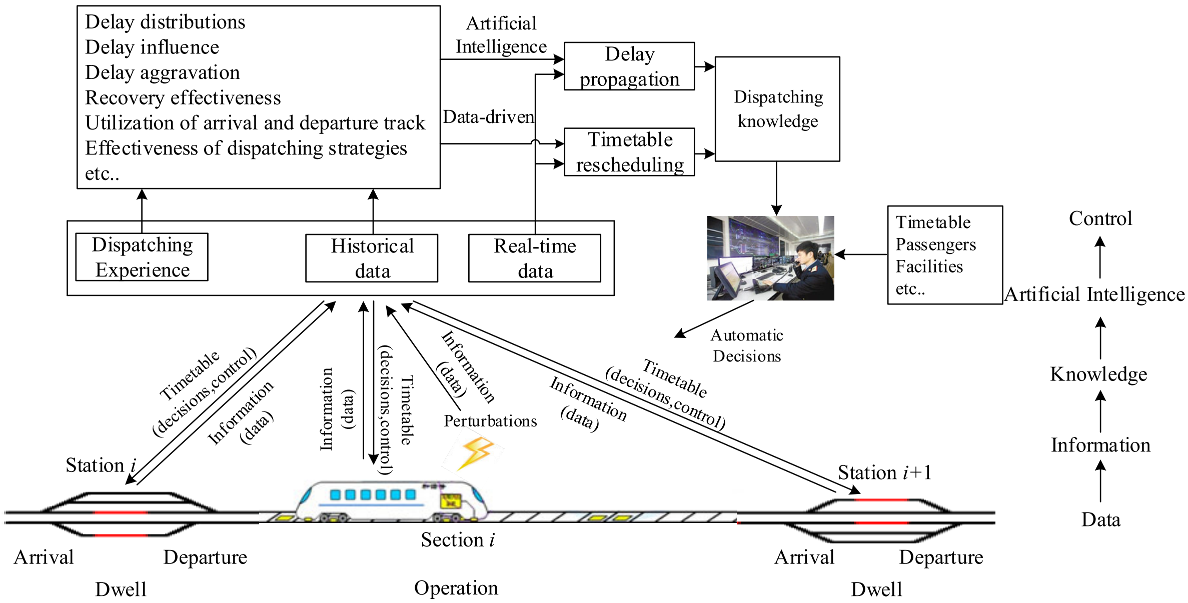

FIGURE 10. Sketch map of intelligent TD.

relationship between buffer time utilization and dispatching strategies, the assessment of the dispatching strategies can be realized [160].

2) INTELLIGENT TD

Intelligent TD is an automated decision-making process in the dispatching system, controlling the train operations. The dispatchers' experience, along with the RWTOD, provides knowledge and dispatching rules regarding the assessing, developing, and protecting of transportation states, making sure that trains always run well. The sketch map of intelligent TD is as shown in Figure 10.

SBB has recently started the rollout of adaptive control system (from German Adaptive Lenkung, adaptive train control) on their network since 2014 [181], [182]. However, the predictive dispatching is needed to be carried out, by considering the disturbances, estimating the running times and the potential conflicts, and predicting the delay occurrence. The distributional model and propagation of delays can be used as a predictive tool by the dispatchers to assess the delay duration and their influences, given certain operation circumstances. With new train operation data, the models can be updated via a dynamic or predicting system for delays. This work is to establish a predictive dispatching decision support tool to help dispatchers in managing train operations.

The development of the intelligent TD will need to address the concerns of dispatching-knowledge extracting, automatic decision-making, and the assessments of dispatchers and their actions taken during train operation control. These measures would eventually contribute to the state-of-the-art, intelligent dispatching systems, enriching the theories and practice of timetable design and real-time train operation adjustment.

The intelligent TD is a critical point of intelligent train operation. Based on large-scale and complex train operation data, various advanced data science and artificial intelligence methods will be synthetically used to study the closed-loop control problem of intelligent traffic control, involving train-state assessment and deduction, train rescheduling, collaborative dispatching, emergency management, and train operating state protection. A study of the train operating state assessment and developing theories based on the multi-driven of time and events is also needed. Also, train delay propagation and recovery mechanisms are required to be revealed; data-driven train delay recovery and intelligent train rescheduling methods in various scenarios are needed to be established; and knowledge automation of intelligent train reschedulings, such as delay propagation knowledge, CDR rules, BTA schemes, and effectiveness of certain dispatching strategies, are needed to be constructed. These research area can provide the theoretical and technical support to the intelligent train dispatching and subsequently, the railway transportation science.

V. CONCLUSIONS

Rail system performance depends on carefully designed timetables and effective real-time train operations control. In this regard, train dispatching plays an indispensable role in train operation management. Train dispatchers deal with collecting and processing train operation information, estimating the status of trains, resolving conflicts, and rescheduling the timetable. Train operation records from train monitoring and describer systems have been valuable sources for analyzing railway performance and assessing the QoS of railways to provide feedback on train operations and improve the planning and control of dense railway networks.

To support dispatchers in decision making, various models have been proposed from which this study surveyed data-driven models and methodologies. Through the review of the relevant literature, drawbacks in train dispatching were found in the mathematical- and simulation- model-driven methods. However, the data-driven models based on train operation records can generate different solutions to support the decision-making of dispatchers. Usually, statistical analysis is employed to reveal some fundamental rules of TD or dependencies between related factors within the CI and ML models. CI is used to generate knowledge for TD or deriving the status of trains. ML models have shown potentials in the field of railway engineering, especially for delay prediction. In bridging the gap between theories and practices in TD, although DDMs have been applied, several research challenges remain in establishing innovative dispatching decisions to help dispatchers in managing train operations. Although DDMs can be useful in solving practical problems or modeling a specific system or procedure, a contemporary trend is to establish hybrid models that combine DDMs and traditional mathematical models. As reviewed in [183], the model-driven DL approach that combines model- and data-driven DL approaches can retain advantages (i.e., determinacy and theoretical soundness) of the model-driven approach and avoid the requirement for accurate modeling. Model-driven approaches have been proven to have a significant level of accuracy, relying on the objective, physical mechanism, and domain knowledge for a specific task. However, their level of generalization is limited in practice. Meanwhile, ML/DL approaches use a standard network architecture as a black box, highly relying on big data to train the black box. Model- and data-driven approaches do not oppose each other. Moreover, the model-driven DL approach can retain the powerful learning ability of the DL approach and overcome the difficulties in network topology selection. We believe that the model-driven DL approach can be widely applied in TD and the other works associated with train operation and management. Given that ML/DL approaches have shown promising abilities in data processing and modeling, they can be applied in TD modeling and classifying delays, modeling the delay propagation, solving the problems of CDR, and optimizing the BTA.

Big data analytics is at its nascent stage; a future research direction is to develop a decision support system for a network-wide RTC to continuously supervise trains that run on the network and update the operating timetable. Advanced and intelligent RTC systems are intended to monitor, predict, and control trains in real time to ensure the safety, regularity, reliability, and punctuality of train operations.

ACKNOWLEDGMENT

The authors gratefully acknowledge the useful contributions made by our project partners in the China Railway Guangzhou Group Company Ltd.

REFERENCES

[1] L.-G. Mattsson, "Railway capacity and train delay relationships," in *Critical Infrastructure*. Berlin, Germany: Springer, 2007, pp. 129–150.

[2] L. Peppard and V. Gourishankar, "Optimal control of a string of moving vehicles," *IEEE Trans. Autom. Control*, vol. AC-15, no. 3, pp. 386–387, Jun. 1970.

[3] E. Quaglietta, P. Pellegrini, R. M. P. Goverde, T. Albrecht, B. Jaekel, G. Marliére, J. Rodriguez, T. Dollevoet, B. Ambrogio, D. Carcasole, M. Giaroli, and G. Nicholson, "The ON-TIME real-time railway traffic management framework: A proof-of-concept using a scalable standardised data communication architecture," *Transp. Res. C, Emerg. Technol.*, vol. 63, pp. 23–50, Feb. 2016.

[4] City University of Hong Kong. (2016). *Safety, Reliability, and Disruption Management of High Speed Rail and Metro Systems*. [Online]. Available: http://www.cityu.edu.hk/csie/TBRS/about/introduction/

[5] M. Velasquez and P. T. Hester, "An analysis of multi-criteria decision making methods," *Int. J. Oper. Res.*, vol. 10, no. 2, pp. 56–66, 2013.

[6] L. Lamorgese, C. Mannino, D. Pacciarelli, and J. T. Krasemann, "Train dispatching," in *Handbook of Optimization in the Railway Industry*. Cham, Switzerland: Springer, 2018, pp. 265–283.

[7] V. Cacchiani, D. Huisman, M. Kidd, L. Kroon, P. Toth, L. Veelenturf, and J. Wagenaar, "An overview of recovery models and algorithms for real-time railway rescheduling," *Transp. Res. B, Methodol.*, vol. 63, pp. 15–37, May 2014.

[8] F. Corman and L. Meng, "A review of online dynamic models and algorithms for railway traffic management," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 3, pp. 1274–1284, Jun. 2015.

[9] A. Thaduri, D. Galar, and U. Kumar, "Railway assets: A potential domain for big data analytics," *Procedia Comput. Sci.*, vol. 53, pp. 457–467, Jan. 2015.

[10] F. Ghofrani, Q. He, R. M. P. Goverde, and X. Liu, "Recent applications of big data analytics in railway transportation systems: A survey," *Transp. Res. C, Emerg. Technol.*, vol. 90, pp. 226–246, May 2018.

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

[12] D. Thorleuchter and D. Van den Poel, "Web mining based extraction of problem solution ideas," *Expert Syst. Appl.*, vol. 40, no. 10, pp. 3961–3969, Aug. 2013.

[13] E. Cambria, B. Schuller, Y. Xia, and C. Havasi, "New avenues in opinion mining and sentiment analysis," *IEEE Intell. Syst.*, vol. 28, no. 2, pp. 15–21, Mar. 2013.

[14] J. Tutcher, "Ontology-driven data integration for railway asset monitoring applications," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Oct. 2014, pp. 85–95.

[15] Y. Ochiai, J. Nishimura, and N. Tomii, "Punctuality analysis by the microscopic simulation and visualization of Web-based train information system data," *WIT Trans. Built Environ.*, vol. 135, pp. 537–549, Jun. 2014.

[16] R. M. P. Goverde and I. A. Hansen, "TNV-prepare: Analysis of Dutch railway operations based on train detection data," *Comput. Railways*, vol. 7, no. 1, pp. 779–788, 2000.

[17] T. Graffagnino, "Ensuring timetable stability with train traffic data," in *Computers in Railways XIII: Computer System Design and Operation in the Railway and Other Transit Systems*. Southampton, U.K.: WIT Press, 2013, pp. 427–438.

[18] S. De Fabris, G. Longo, and G. Medeossi, "Automated analysis of train event recorder data to improve micro-simulation models," in *Timetable Planning and Information Quality*. 2010, pp. 125–134.

[19] A. Nash and M. Ullius, "Optimizing railway timetables with opentimetable," *WIT Trans. Built Environ.*, vol. 74, pp. 637–646, Feb. 2004.

[20] L. Oneto, E. Fumeo, G. Clerico, R. Canepa, F. Papa, C. Dambra, N. Mazzino, and D. Anguita, "Train delay prediction systems: A big data analytics perspective," *Big Data Res.*, vol. 11, pp. 54–64, Mar. 2018.

[21] F. Cerreto, O. A. Nielsen, S. Harrod, and B. F. Nielsen, "Causal analysis of railway running delays," in *Proc. 11th World Congr. Railway Res. (WCRR)*, Jun. 2016, p. 7.

[22] J. Wallander and M. Mäkitalo, "Data mining in rail transport delay chain analysis," *Int. J. Shipping Transp. Logistics*, vol. 4, no. 3, pp. 269–285, 2012.

[23] D. Jaroszweski, E. Hooper, C. Baker, L. Chapman, and A. Quinn, "The impacts of the 28 June 2012 storms on UK road and rail transport," *Meteorolog. Appl.*, vol. 22, no. 3, pp. 470–476, Jul. 2015.

[24] M. Komori and N. Tomii, "Visualization of train traffic records to realize more robust timetable," in *Proc. 1st Asian Conf. Railway Infrastruct. Transp.*, Jeju, South Korea, 2016, pp. 235–238.

[25] H. Khadilkar, "Data-enabled stochastic modeling for evaluating schedule robustness of railway networks," *Transp. Sci.*, vol. 51, no. 4, pp. 1161–1176, 2016.

[26] I. Şahin, "Markov chain model for delay distribution in train schedules: Assessing the effectiveness of time allowances," *J. Rail Transp. Planning Manage.*, vol. 7, no. 3, pp. 101–113, Dec. 2017.
[27] M. F. Gorman, "Statistical estimation of railroad congestion delay," *Transp. Res. E, Logistics Transp. Rev.*, vol. 45, no. 3, pp. 446–456, May 2009.
[28] S. Milinković, M. Marković, S. Vesković, M. Ivić, and N. Pavlović, "A fuzzy Petri net model to estimate train delays," *Simul. Model. Pract. Theory*, vol. 33, pp. 144–157, Apr. 2013.
[29] C. Wen, Z. Li, J. Lessan, L. Fu, P. Huang, and C. Jiang, "Statistical investigation on train primary delay based on real records: Evidence from Wuhan–Guangzhou HSR," *Int. J. Rail Transp.*, vol. 5, no. 3, pp. 170–189, Mar. 2017.
[30] J. C. Jong, T. H. Lin, C. K. Lee, and H. L. Hu, "The analysis of train reliability for the Taiwan high speed rail," *WIT Trans. Built Environ.*, vol. 114, pp. 169–180, Jul. 2010.
[31] A. D'Ariano, and M. Pranzo, "An advanced real-time train dispatching system for minimizing the propagation of delays in a dispatching area under severe disturbances," *Netw. Spatial Econ.*, vol. 9, no. 1, pp. 63–84, Mar. 2009.
[32] F. Corman and A. D'Ariano, "Assessment of advanced dispatching measures for recovering disrupted railway traffic situations," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2289, no. 1, pp. 1–9, Jan. 2012.
[33] W. Fang, S. Yang, and X. Yao, "A survey on problem models and solution approaches to rescheduling in railway networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 6, pp. 2997–3016, Dec. 2015.
[34] M. J. C. M. Vromans, R. Dekker, and L. G. Kroon, "Reliability and heterogeneity of railway services," *Eur. J. Oper. Res.*, vol. 172, no. 2, pp. 647–665, Jul. 2006.
[35] X. Delorme, X. Gandibleux, and J. Rodriguez, "Stability evaluation of a railway timetable at station level," *Eur. J. Oper. Res.*, vol. 195, no. 3, pp. 780–790, Jun. 2009.
[36] R. M. P. Goverde and L. Meng, "Advanced monitoring and management information of railway operations," *J. Rail Transp. Planning Manage.*, vol. 1, no. 2, pp. 69–79, Dec. 2011.
[37] C. Wen, J. Li, Q. Peng, B. Li, and J. Ren, "Predicting high-speed train operation conflicts using workflow nets and triangular fuzzy numbers," *Proc. Inst. Mech. Eng., F, J. Rail Rapid Transit*, vol. 229, no. 3, pp. 268–279, Mar. 2015.
[38] M. Giuliari, F. Pellegrini, and S. Savio, "Moving block and traffic management in railway applications: The EU project COMBINE," *WIT Trans. Built Environ.*, vol. 50, pp. 11–20, Aug. 2000.
[39] P. Kecman and R. M. Goverde, "Process mining of train describer event data and automatic conflict identification," in *Computers in Railways XIII* (WIT Transactions on the Built Environment), vol. 127. Southampton, U.K.: WIT Press, 2013, pp. 227–238.
[40] I. Şahin, "Railway traffic control and train scheduling based oninter-train conflict management," *Transp. Res. B, Methodol.*, vol. 33, no. 7, pp. 511–534, Sep. 1999.
[41] P. Jovanović, P. Kecman, N. Bojović, and D. Mandić, "Optimal allocation of buffer times to increase train schedule robustness," *Eur. J. Oper. Res.*, vol. 256, no. 1, pp. 44–54, Jan. 2017.
[42] D. Solomatine, L. M. See, and R. J. Abrahart, "Data-driven modelling: Concepts, approaches and experiences," in *Practical Hydroinformatics*. Berlin, Germany: Springer, 2009, pp. 17–30.
[43] J. Zhang, F.-Y. Wang, K. Wang, W.-H. Lin, X. Xu, and C. Chen, "Data-driven intelligent transportation systems: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 4, pp. 1624–1639, Dec. 2011.
[44] C. Roberts, J. M. Easton, A. V. S. Kumar, and S. Kohli, *Innovative Applications of Big Data in the Railway Industry*. Philadelphia, PA, USA: IGI Global, 2017.
[45] A. Nash and D. Huerlimann, "Railroad simulation using opentrack," *WIT Trans. Built Environ.*, vol. 74, pp. 45–54, May 2004.
[46] J. P. Bendfeldt, U. Mohr, and L. Muller, "RailSys, a system to plan future railway needs," *WIT Trans. Built Environ.*, vol. 50, pp. 249–255, Aug. 2000.
[47] I. A. Hansen, R. M. P. Goverde, and D. J. van der Meer, "Online train delay recognition and running time prediction," in *Proc. 13th Int. IEEE Conf. Intell. Transp. Syst.*, Sep. 2010, pp. 1783–1788.
[48] J. Yuan and I. A. Hansen, "Optimizing capacity utilization of stations by estimating knock-on train delays," *Transp. Res. B, Methodol.*, vol. 41, no. 2, pp. 202–217, Feb. 2007.
[49] H. Flier, R. Gelashvili, T. Graffagnino, and M. Nunkesser, "Mining railway delay dependencies in large-scale real-world delay data," in *Robust and Online Large-Scale Optimization*. Berlin, Germany: 2009, pp. 354–368.
[50] T. Richter, "Systematic analyses of train run deviations from the timetable," *WIT Trans. Built Environ.*, vol. 114, pp. 651–662, Jul. 2010.
[51] C. Jiang, P. Huang, J. Lessan, L. Fu, and C. Wen, "Forecasting primary delay recovery of high-speed railway using multiple linear regression, supporting vector machine, artificial neural network, and random forest regression," *Can. J. Civil Eng.*, vol. 46, no. 5, pp. 353–363, Mar. 2018.
[52] C. Turner, A. Tiwari, A. Starr, and K. Blacktop, "A review of key planning and scheduling in the rail industry in Europe and UK," *Proc. Inst. Mech. Eng.*, vol. 230, no. 3, pp. 984–998, 2016.
[53] C. Conte, "Identifying dependencies among delays," Ph.D. dissertation, Oper. Res., Georg-August Univ. Göttingen, Göttingen, Germany, 2008.
[54] N. O. E. Olsson and H. Haugland, "Influencing factors on train punctuality—Results from some norwegian studies," *Transp. Policy*, vol. 11, no. 4, pp. 387–397, Oct. 2004.
[55] C.-W. Palmqvist, N. Olsson, and L. Hiselius, "Some influencing factors for passenger train punctuality in Sweden," in *Proc. Annu. Conf. Prognostics Health Manage. Soc.*, vol. 8, pp. 1–13, 2017.
[56] W. Brazil, A. White, M. Nogal, B. Caulfield, A. O'Connor, and C. Morton, "Weather and rail delays: Analysis of metropolitan rail in Dublin," *J. Transp. Geogr.*, vol. 59, pp. 69–76, Feb. 2017.
[57] M. Veiseth, N. Olsson, and I. A. F. Saetermo, "Infrastructure's influence on rail punctuality," *WIT Trans. Built Environ.*, vol. 96, pp. 481–489, Jul. 2007.
[58] S. Gibson, G. Cooper, and B. Ball, "Developments in transport policy: The evolution of capacity charges on the UK rail network," *J. Transp. Econ. Policy*, vol. 36, no. 2, pp. 341–354, May 2002.
[59] N. Hasan, "Direct fixation fastener (Dff) spacing and stiffness design," in *Proc. Joint Rail Conf.*, Jan. 2011, pp. 11–17.
[60] P. Xu, F. Corman, and Q. Peng, "Analyzing railway disruptions and their impact on delayed traffic in Chinese high-speed railway," *IFAC-PapersOnLine*, vol. 49, no. 3, pp. 84–89, Jan. 2016.
[61] K. Ushida, S. Makino, and N. Tomii, "Increasing robustness of dense timetables by visualization of train traffic record data and Monte Carlo simulation," in *Proc. World Congr. Railway Res. (WCRR)*, Lille, France, May 2011, pp. 1–12.
[62] K. Porter and K. Ramer, "Estimating earthquake-induced failure probability and downtime of critical facilities," *J. Bus. Continuity Emergency Planning*, vol. 5, no. 4, pp. 352–364, 2012.
[63] P. Liu, L. Yang, Z. Gao, S. Li, and Y. Gao, "Fault tree analysis combined with quantitative analysis for high-speed railway accidents," *Saf. Sci.*, vol. 79, pp. 344–357, Nov. 2015.
[64] J. Ma, Y. Bai, J. Shen, and F. Zhou, "Examining the impact of adverse weather on urban rail transit facilities on the basis of fault tree analysis and fuzzy synthetic evaluation," *J. Transp. Eng.*, vol. 140, no. 3, Mar. 2014, Art. no. 04013011.
[65] H. Li, D. Parikh, Q. He, B. Qian, Z. Li, D. Fang, and A. Hampapur, "Improving rail network velocity: A machine learning approach to predictive maintenance," *Transp. Res. C, Emerg. Technol.*, vol. 45, pp. 17–26, Aug. 2014.
[66] L. Oneto, E. Fumeo, G. Clerico, R. Canepa, F. Papa, C. Dambra, N. Mazzino, and D. Anguita, "Advanced analytics for train delay prediction systems by including exogenous weather data," in *Proc. IEEE Int. Conf. Data Sci. Adv. Anal. (DSAA)*, Oct. 2016, pp. 458–467.
[67] W.-H. Lee, L.-H. Yen, and C.-M. Chou, "A delay root cause discovery and timetable adjustment model for enhancing the punctuality of railway services," *Transp. Res. C, Emerg. Technol.*, vol. 73, pp. 49–64, Dec. 2016.
[68] A. Yamamura, M. Koresawa, S. Adachi, and N. Tomii, "Taking effective delay reduction measures and using delay elements as indices for Tokyo's metropolitan railways," in *Computers in Railways XIV: Railway Engineering Design and Optimization*, vol. 135. Southampton, U.K.: WIT Press, 2014, pp. 3–15.
[69] F. Cerreto, B. F. Nielsen, O. A. Nielsen, and S. S. Harrod, "Application of data clustering to railway delay pattern recognition," *J. Adv. Transp.*, vol. 2018, Mar. 2018, Art. no. 6164534.
[70] B. Adenso-Díaz, M. O. González, and P. González-Torre, "On-line timetable re-scheduling in regional train services," *Transp. Res. B, Methodol.*, vol. 33, no. 6, pp. 387–398, Aug. 1999.
[71] L. Oneto, E. Fumeo, G. Clerico, R. Canepa, F. Papa, C. Dambra, N. Mazzino, and D. Anguita, "Dynamic delay predictions for large-scale railway networks: Deep and shallow extreme learning machines tuned via thresholdout," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 47, no. 10, pp. 2574–2767, Oct. 2017.

[72] T. Richter, "Data aggregation for detailed analysis of train delays," in *Computers in Railways XIII: Computer System Design and Operation in the Railway and Other Transit Systems*, vol. 127. 2013, p. 239.

[73] M. Carey and A. Kwieciński, "Stochastic approximation to the effects of headways on knock-on delays of trains," *Transp. Res. B, Methodol.*, vol. 28, no. 4, pp. 251–267, Aug. 1994.

[74] R. M. Goverde, I. A. Hansen, G. Hooghiemstra, and H. P. Lopuhaa, "Delay distributions in railway stations," in *Proc. 9th World Conf. Transp. Res.*, Seoul, South Korea, Jul. 2001, pp. 1–14.

[75] J. Yuan, "Statistical analyses of train delays at the Hague HS," in *Proc. Train Delays Stations Netw. Stability (Workshop)*, Delft, The Netherlands, 2001, pp. 975–984.

[76] T. Huisman, R. J. Boucherie, and N. M. van Dijk, "A solvable queueing network model for railway networks and its validation and applications for The Netherlands," *Eur. J. Oper. Res.*, vol. 142, no. 1, pp. 30–51, Oct. 2002.

[77] K. Briggs and C. Beck, "Modelling train delays with q-exponential functions," *Phys. A, Stat. Mech. Appl.*, vol. 378, no. 2, pp. 498–504, May 2007.

[78] J. Yuan, R. Goverde, and I. Hansen, "Propagation of train delays in stations," *WIT Trans. Built Environ.*, vol. 61, pp. 975–984, May 2002.

[79] J. Yuan, "Stochastic modelling of train delays and delay propagation in stations," Eburon, Utrecht, The Netherlands, Tech. Rep., 2006.

[80] T. Büker and B. Seybold, "Stochastic modelling of delay propagation in large networks," *J. Rail Transp. Planning Manage.*, vol. 2, no. 1, pp. 34–50, Nov./Dec. 2012.

[81] C. Wen, Z. Li, J. Lessan, L. Fu, P. Huang, C. Jiang, and M. I. Muresan, "Analysis of causes and effects of primary delays in a high-speed rail system," in *Proc. 97th Transp. Res. Board Annu. Meeting*, Washington, DC, USA, 2018.

[82] J. Lessan, L. Fu, C. Wen, P. Huang, and C. Jiang, "Stochastic model of train running time and arrival delay: A case study of Wuhan–Guangzhou high-speed rail," *J. Transp. Res. Board*, vol. 2672, no. 10, pp. 215–223, 2018.

[83] S. Harrod, G. Pournaras, and B. F. Nielsen, "Distribution fitting for very large railway delay data sets with discrete values," in *Proc. Annu. Transp. Conf. Aalborg Univ.*, Aalborg, Denmark, 2018.

[84] D. J. Van der Meer, R. M. Goverde, and I. A. Hansen, "Prediction of train running times using historical track occupation data," in *Proc. WCTR*, 2009, p. 22.

[85] A. Zilko, A. Hanea, D. Kurowicka, and R. Goverde, "Non-parametric Bayesian network to forecast railway disruption lengths," in *Proc. 2nd Int. Conf. Railway Technol., Res., Develop. Maintenance (Railways)*, Ajaccio, France, Apr. 2014.

[86] Y. Cui, U. Martin, and W. Zhao, "Calibration of disturbance parameters in railway operational simulation based on reinforcement learning," *J. Rail Transp. Planning Manage.*, vol. 6, no. 1, pp. 1–12, Jun. 2016.

[87] N. Meng-Cheng, T. Kwok-Leung, and Z. Yang, "A data driven method for delay duration estimation of high speed train," in *Proc. 97th Transp. Res. Board Annu. Meeting*, Washington, DC, USA, 2018.

[88] Y. Tang, C. Wen, P. Huang, J. Li, and Y. Yang, "Support vector regression models for influenced time prediction in high-speed rail system," in *Proc. 97th Transp. Res. Board Annu. Meeting*, Washington, DC, USA, 2018.

[89] *International Union of Railways, Assessment of the Performance of the Network Related to Rail Traffic Operation for the Purpose of Quality Analyses-Delay Coding and Delay Cause Attribution Process*, UIC, Paris, France, 2009.

[90] C. S. Chang and B. S. Thia, "Online rescheduling of mass rapid transit systems: Fuzzy expert system approach," *IEE Proc.-Electr. Power Appl.*, vol. 143, no. 4, pp. 307–316, Jul. 1996.

[91] L. E. Meester and S. Muns, "Stochastic delay propagation in railway networks and phase-type distributions," *Transp. Res. B, Methodol.*, vol. 41, no. 2, pp. 218–230, Feb. 2007.

[92] P. Wiggenraad, "Alighting and boarding times of passengers at Dutch railway stations," TRAIL Res. School, Delft, The Netherlands, Tech. Rep., 2001.

[93] S. Buchmueller, U. Weidmann, and A. Nash, "Development of a dwell time calculation model for timetable planning," *WIT Trans. Built Environ.*, vol. 103, pp. 525–534, Sep. 2008.

[94] P. Murali, M. Dessouky, F. Ordóñez, and K. Palmer, "A delay estimation technique for single and double-track railroads," *Transp. Res. E, Logistics Transp. Rev.*, vol. 46, no. 4, pp. 483–495, Jul. 2010.

[95] J. Guo, L. Meng, P. Kecman, and F. Corman, "Modeling delay relations based on mining historical train monitoring data: A Chinese railway case," in *Proc. 6th Int. Conf. Railway Oper. Modelling Anal. (RailTokyo)*, 2015, pp. 1–28.

[96] H. Flier, T. Graffagnino, and M. Nunkesser, "Finding robust train paths in dense corridors," in *Proc. 3rd Int. Seminar Railway Oper. Modeling Anal. RailZurich*, 2009, pp. 1–18.

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

[98] D. Li, W. Daamen, and R. M. P. Goverde, "Estimation of train dwell time at short stops based on track occupation event data: A study at a Dutch railway station," *J. Adv. Transp.*, vol. 50, no. 5, pp. 877–896, Aug. 2016.

[99] K. Fukami, H. Yamamoto, T. Hatanaka, and T. Terada, "A new delay forecasting system for the passenger information control system (PIC) of the Tokaido-Sanyo Shinkansen," in *Proc. 10th Int. Conf.*, vol. 1, 2006, pp. 199–203.

[100] P. Kecman and R. M. Goverde, "Online data-driven adaptive prediction of train event times," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 1, pp. 465–474, Feb. 2015.

[101] A. D'Ariano, D. Pacciarelli, and M. Pranzo, "A branch and bound algorithm for scheduling trains in a railway network," *Eur. J. Oper. Res.*, vol. 183, no. 2, pp. 643–657, Dec. 2007, 2007.

[102] A. D'Ariano, and T. Albrecht, "Running time re-optimization during real-time timetable perturbations," *WIT Trans. Built Environ.*, vol. 40, no. 1, pp. 147–156, 2010.

[103] J. Barta, A. E. Rizzoli, M. Salani, and L. M. Gambardella, "Statistical modelling of delays in a rail freight transportation network," in *Proc. Winter Simulation Conf. (WSC)*, Dec. 2012, pp. 1–12.

[104] P. Kecman, F. Corman, and L. Meng, "Train delay evolution as a stochastic process," in *Proc. 6th Int. Conf. Railway Oper. Modeling Anal.-RailTokyo*, 2015, pp. 1–19.

[105] S. L. Wang and J. H. Ma, "Variable-carriage vehicle scheduling based on segment point," in *Proc. Int. Conf. Comput. Sci. Artif. Intell. (ICCSAI)*, 2013, pp. 16–20.

[106] Y.-H. Cheng and L.-A. Yang, "A fuzzy Petri nets approach for railway traffic control in case of abnormality: Evidence from Taiwan railway system," *Expert Syst. Appl.*, vol. 36, no. 4, pp. 8040–8048, May 2009.

[107] C. Wen, Q. Peng, Y. Chen, and J. Ren, "Modelling the running states of high-speed trains using triangular fuzzy number workflow nets," *Proc. Inst. Mech. Eng., F, J. Rail Rapid Transit*, vol. 228, no. 4, pp. 422–430, May 2014.

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

[109] J. Lessan, L. Fu, and C. Wen, "A hybrid Bayesian network model for predicting delays in train operations," *Comput. Ind. Eng.*, vol. 127, pp. 1214–1222, Jan. 2019.

[110] L. J. Martin, "Predictive reasoning and machine learning for the enhancement of reliability in railway systems," in *Proc. Int. Conf. Rel., Saf., Secur. Railway Syst.* Cham, Switzerland: Springer, 2016, pp. 178–188.

[111] L. J. Martin and A. Romanovsky, "A formal approach to designing reliable advisory systems," in *Proc. Int. Workshop Softw. Eng. Resilient Syst.* Cham, Switzerland: Springer, 2016, pp. 28–42.

[112] A. Lulli, L. Oneto, R. Canepa, S. Petralli, and D. Anguita, "Large-scale railway networks train movements: A dynamic, interpretable, and robust hybrid data analytics system," in *Proc. IEEE 5th Int. Conf. Data Sci. Adv. Anal. (DSAA)*, Oct. 2018, pp. 371–380.

[113] S. Pongnumkul, T. Pechprasarn, N. Kunaseth, and K. Chaipah, "Improving arrival time prediction of Thailand's passenger trains using historical travel times," in *Proc. 11th Int. Joint Conf. Comput. Sci. Softw. Eng. (JCSSE)*, May 2014, pp. 307–312.

[114] J. Peters, B. Emig, M. Jung, and S. Schmidt, "Prediction of delays in public transportation using neural networks," in *Proc. Int. Conf. Comput. Intell. Modelling, Control Automat. Int. Conf. Intell. Agents, Web Technol. Internet Commerce (CIMCA-IAWTIC)*, vol. 2, Nov. 2005, pp. 92–97.

[115] M. Yaghini, M. M. Khoshraftar, and M. Seyedabadi, "Railway passenger train delay prediction via neural network model," *J. Adv. Transp.*, vol. 47, no. 3, pp. 355–368, Apr. 2013.

[116] N. Marković, S. Milinković, K. S. Tikhonov, and P. Schonfeld, "Analyzing passenger train arrival delays with support vector regression," *Transp. Res. C, Emerg. Technol.*, vol. 56, pp. 251–262, Jul. 2015.

[117] W. Barbour, J. C. M. Mori, S. Kuppa, and D. B. Work, "Prediction of arrival times of freight traffic on US railroads using support vector regression," *Transp. Res. C, Emerg. Technol.*, vol. 93, pp. 211–227, Aug. 2018.

[118] D. Chen, L. Wang, and L. Li, "Position computation models for high-speed train based on support vector machine approach," *Appl. Soft Comput.*, vol. 30, pp. 758–766, May 2015.
[119] M. S. Visentini, D. Borenstein, J.-Q. Li, and P. B. Mirchandani, "Review of real-time vehicle schedule recovery methods in transportation services," *J. Scheduling*, vol. 17, no. 6, pp. 541–567, Dec. 2014.
[120] H. Naohiko, N. Osamu, M. Shigeru, I. Hitoshi, and T. Norio, "Recovery measure of disruption in train operation in Tokyo Metropolitan Area," *Transp. Res. Procedia*, vol. 25, pp. 4374–4384, Jan. 2017.
[121] C. Liebchen, M. Lübbecke, R. Möhring, and S. Stiller, "The concept of recoverable robustness, linear programming recovery, and railway applications," in *Robust and Online Large-Scale Optimization*. Berlin, Germany: Springer, 2009, pp. 1–27.
[122] L. Cadarso, Á. Marín, and G. Maróti, "Recovery of disruptions in rapid transit networks," *Transp. Res. E, Logistics Transp. Rev.*, vol. 53, pp. 15–33, Jul. 2013.
[123] L. Cadarso and Á. Marín, "Recovery of disruptions in rapid transit networks with origin-destination demand," *Procedia-Social Behav. Sci.*, vol. 111, pp. 528–537, Feb. 2014.
[124] C. Wen, J. Lessan, L. Fu, P. Huang, and C. Jiang, "Data-driven models for predicting delay recovery in high-speed rail," in *Proc. 4th Int. Conf. Transp. Inf. Saf. (ICTIS)*, Aug. 2017, pp. 144–151.
[125] L. Bottou, "Large-scale machine learning with stochastic gradient descent," in *Proc. COMPSTAT*. Springer, 2010, pp. 177–186.
[126] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: A new learning scheme of feedforward neural networks," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, Jul. 2014, pp. 985–990.
[127] C. Wen, "Train operation conflict management research status of high-speed railways," *J. Transp. Secur.*, vol. 4, no. 3, pp. 231–246, Sep. 2011.
[128] B. Chen and P. T. Harker, "Two moments estimation of the delay on single-track rail lines with scheduled traffic," *Transp. Sci.*, vol. 24, no. 4, pp. 261–275, Nov. 1990.
[129] A. Higgins, E. Kozan, and L. Ferreira, "Modelling delay risks associated with train schedules," *Transp. Planning Technol.*, vol. 19, no. 2, pp. 89–108, 1995.
[130] L. Ferreira and A. Higgins, "Modeling reliability of train arrival times," *J. Transp. Eng.*, vol. 122, no. 6, pp. 414–420, Nov. 1996.
[131] G. Medeossi, G. Longo, and S. de Fabris, "A method for using stochastic blocking times to improve timetable planning," *J. Rail Transp. Planning Manage.*, vol. 1, no. 1, pp. 1–13, Nov. 2011.
[132] G. D'Addio, M. Mazzucchelli, and S. Savio, "Automatic conflict detection and resolution in metrorail systems: Evaluation approach for MARCO EU project," *WIT Trans. Built Environ.*, vol. 33, pp. 461–470, Jan. 1998.
[133] J. S. Hooghiemstra, L. G. Kroon, M. A. Odijk, M. Salomon, and P. J. Zwaneveld, "Decision support systems support the search for win-win solutions in railway network design," *INFORMS J. Appl. Anal.*, vol. 29, no. 2, pp. 15–32, 1999.
[134] M. Giannettoni and S. Savio, "The European project COMBINE 2 to improve knowledge on future rail traffic management systems," *WIT Trans. Built Environ.*, vol. 74, pp. 495–704, May 2004.
[135] A. D'Ariano, M. Pranzo, and I. A. Hansen, "Conflict resolution and train speed coordination for solving real-time timetable perturbations," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 2, pp. 208–222, Jun. 2007.
[136] S. Toriumi, A. Taguchi, and T. Matsumoto, "A model to simulate delay in train schedule caused by crowded passengers: Using a time–space network," *Int. Regional Sci. Rev.*, vol. 37, no. 2, pp. 225–244, 2014.
[137] R. M. Goverde, W. Daamen, and I. A. Hansen, "Automatic identification of route conflict occurrences and their consequences," in *Computers Railways XI*. vol. 103. Southampton, U.K.: WIT Press, 2008, pp. 473–482.
[138] W. Daamen, R. M. Goverde, and I. A. Hansen, "Non-discriminatory automatic registration of knock-on train delays," *Netw. Spatial Econ.*, vol. 9, no. 1, pp. 47–61, Mar. 2009.
[139] H. Schaefer and S. Pferdmenges, "An expert system for real-time train dispatching," *WIT Trans. Built Environ.*, vol. 7, pp. 27–34, Jan. 1994.
[140] T. Chiang, H. Hau, H. M. Chiang, S. Y. Kob, and C. H. Hsieh, "Knowledge-based system for railway scheduling," *Data Knowl. Eng.*, vol. 27, no. 3, pp. 289–312, Oct. 1998.
[141] A. Fay, "A fuzzy knowledge-based system for railway traffic control," *Eng. Appl. Artif. Intell.*, vol. 13, no. 6, pp. 719–729, Dec. 2000.
[142] H. Zhuang, L. Feng, C. Wen, Q. Peng, and Q. Tang, "High-speed railway train timetable conflict prediction based on fuzzy temporal knowledge reasoning," *Engineering*, vol. 2, no. 3, pp. 366–373, Sep. 2016.
[143] B. R. Ke, C. L. Lin, H. H. Chien, H. W. Chiu, and N. Chen, "A new approach for improving the performance of freight train timetabling of a single-track railway system," *Transp. Planning Technol.*, vol. 38, no. 2, pp. 238–264, Apr. 2014.
[144] F. Corman and A. D'Ariano, I. A. Hansen, and D. Pacciarelli, "Optimal multi-class rescheduling of railway traffic," *J. Rail Transp. Planning Manage.*, vol. 1, no. 1, pp. 14–24, Nov. 2011.
[145] M. Mazzarello and E. Ottaviani, "A traffic management system for real-time traffic optimisation in railways," *Transp. Res. B, Methodol.*, vol. 41, no. 2, pp. 246–274, Feb. 2007.
[146] T. Zhu, J. M. Mera, B. Suarez, and J. Maroto, "An agent-based support system for railway station dispatching," *Expert Syst. Appl.*, vol. 61, pp. 39–52, Nov. 2016.
[147] T. Zhu and J. M. M. S. de Pedro, "Railway traffic conflict detection via a state transition prediction approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 5, pp. 1268–1278, May 2017.
[148] J. Yuan and I. A. Hansen, "Closed form expressions of optimal buffer times between scheduled trains at railway bottlenecks," in *Proc. 11th Int. IEEE Conf. Intell. Transp. Syst.*, Oct. 2008, pp. 675–680.
[149] M. Vromans, "Reliability of railway systems," Ph.D. dissertation, Rotterdam School Manage., Erasmus Univ. Rotterdam, Rotterdam, The Netherlands, 2005.
[150] M. Fischetti, D. Salvagnin, and A. Zanette, "Fast approaches to improve the robustness of a railway timetable," *Transp. Sci.*, vol. 43, no. 3, pp. 321–335, Jun. 2009.
[151] E. V. Andersson, A. Peterson, and J. T. Krasemann, "Quantifying railway timetable robustness in critical points," *J. Rail Transp. Planning Manage.*, vol. 3, no. 3, pp. 95–110, Aug. 2013.
[152] L. G. Kroon, R. Dekker, and M. J. C. M. Vromans, "Cyclic railway timetabling: A stochastic optimization approach," in *Algorithmic Methods for Railway Optimization*. Berlin, Germany: Springer, 2007, pp. 41–66.
[153] C.-W. Palmqvist, N. O. Olsson, and L. Hiselius, "An empirical study of timetable strategies and their effects on punctuality," in *Proc. 7th Int. Conf. Railway Oper. Modeling Anal. (Rail Lille)*, 2017, pp. 1–21.
[154] R. M. P. Goverde and I. A. Hansen, "Performance indicators for railway timetables," in *Proc. IEEE Int. Conf. Intell. Rail Transp. Proc.*, Aug./Sep. 2013, pp. 301–306.
[155] *UIC Code 451-1 Timetable Recovery Margins to Guarantee Timekeeping—Recovery Margins*, Int. Union Railways, Paris, France, 2009.
[156] J. Jespersen-Groth, D. Potthoff, J. Clausen, D. Huisman, L. Kroon, G. Maróti, and M. N. Nielsen, "Disruption management in passenger railway transportation," in *Robust and Online Large-Scale Optimization*. Berlin, Germany: Springer, 2009, pp. 399–421.
[157] I. A. Hansen, "Station capacity and stability of train operations," in *Computers in Railways VII*, vol. 7. Southampton, U.K.: WIT Press, 2000, pp. 809–816.
[158] R. Rudolph, "Allowances and margins in railway scheduling," in *Proc. WCRR*, Oct. 2003, pp. 230–238.
[159] P. Vansteenwegen and D. Van Oudheusden, "Developing railway timetables which guarantee a better service," *Eur. J. Oper. Res.*, vol. 173, no. 1, pp. 337–350, 2006.
[160] P. Huang, C. Wen, Q. Peng, J. Lessan, L. Fu, and C. Jiang, "A data-driven time supplements allocation model for train operations on high-speed railways," *Int. J. Rail Transp.*, vol. 7, no. 2, pp. 140–157, 2019.
[161] T. Ho, T. Chen, and C. Chou, "Integrating of optimization and data mining techniques for high-speed train timetable design considering disturbances," *Gerontechnology*, vol. 11, no. 2, pp. 323–329, 2012.
[162] S. Araya, K. Abe, and K. Fukumori, "An optimal rescheduling for online train traffic control in disturbed situations," in *Proc. 22nd IEEE Conf. Decis. Control*, Dec. 2013, pp. 489–494.
[163] K. Komaya and T. Fukuda, "ESTRAC-III: An expert system for train traffic control in disturbed situations," *IFAC Proc. Volumes*, vol. 23, no. 2, pp. 147–153, Sep. 1990.
[164] K. Komaya and T. Fukuda, "A knowledge-based approach for railway scheduling," in *Proc. 7th IEEE Conf. Artif. Intell. Appl.*, vol. 1, Feb. 1991, pp. 404–411.
[165] S. Tsuruta and K. Matsumoto, "A knowledge-based interactive train scheduling system-aiming at large-scale complex planning expert systems," in *Proc. Int. Workshop Artif. Intell. Ind. Appl.*, May 1988, pp. 490–495.
[166] G. Vernazza and R. Zunino, "A distributed intelligence methodology for railway traffic control," *IEEE Trans. Veh. Technol.*, vol. 39, no. 3, pp. 263–270, Aug. 1990.
[167] J. Lange and F. Werner, "Approaches to modeling train scheduling problems as job-shop problems with blocking constraints," *J. Scheduling*, vol. 21, no. 2, pp. 191–207, Apr. 2018.
[168] P. Priore, D. De La Fuente, A. Gomez, and J. Puente, "A review of machine learning in dynamic scheduling of flexible manufacturing systems," *Artif. Intell. Eng. Des. Anal. Manuf.*, vol. 15, pp. 251–263, Jul. 2001.

[169] P. Priore, A. Gómez, R. Pino, and R. Rosillo, "Dynamic scheduling of manufacturing systems using machine learning: An updated review," *AI EDAM*, vol. 28, no. 1, pp. 83–97, Feb. 2014.
[170] H. Ingimundardottir and T. P. Runarsson, "Discovering dispatching rules from data using imitation learning: A case study for the job-shop problem," *J. Scheduling*, vol. 21, no. 4, pp. 413–428, Aug. 2018.
[171] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proc. IEEE*, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.
[172] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, "Greedy layer-wise training of deep networks," in *Proc. Adv. Neural Inf. Process. Syst.*, 2007, pp. 153–160.
[173] J. L. Elman, "Finding structure in time," *Cognit. Sci.*, vol. 14, no. 2, pp. 179–211, Mar. 1990.
[174] Y. Duan, Y. Lv, and F.-Y. Wang, "Travel time prediction with LSTM neural network," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2016, pp. 1053–1058.
[175] R. D. Raut and V. K. Goyal, "Public transport bus arrival time prediction with seasonal and special emphasis on weather compensation changes using RNN," *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 1, no. 6, pp. 378–382, Aug. 2012.
[176] K. Gopalakrishnan and H. Balakrishnan, "A comparative analysis of models for predicting delays in air traffic networks," in *Proc. 12th USA/Europe Air Traffic Manage. Res. Develop. Seminar (ATM)*, 2017, pp. 1–10.
[177] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, p. 436, 2015.
[178] K. Lin, R. Zhao, Z. Xu, and J. Zhou, "Efficient large-scale fleet management via multi-agent deep reinforcement learning," in *Proc. 24th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2018, pp. 1774–1783.
[179] Z. Mo, "Deep learning for subway pedestrian forecast based on node camera," *Adv. Transp. Stud.*, vol. 2, pp. 31–44, Nov. 2017.
[180] W. Chen, Y. Xu, and X. Wu, "Deep reinforcement learning for multi-resource multi-machine job scheduling," 2017, *arXiv:1711.07440*. [Online]. Available: https://arxiv.org/abs/1711.07440
[181] M. Voelker, "Adaptive Lenkung bei den SBB," in *Proc. IT13.rail*, Hamburg, German, 2013.
[182] A. Toletti, V. De Martinis, and U. Weidmann, "What about train length and energy efficiency of freight trains in rescheduling models?" *Transp. Res. Procedia*, vol. 10, pp. 584–594, Jan. 2015.
[183] Z. Xu and J. Sun, "Model-driven deep-learning," *Nat. Sci. Rev.*, vol. 5, no. 1, pp. 22–24, Jan. 2017.

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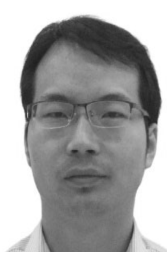

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