Handling uncertainty in train timetable rescheduling
A review of the literature and future research directions

Zhan, Shuguang; Xie, Jiemin; Wong, S. C.; Zhu, Yongqiu; Corman, Francesco

DOI
10.1016/j.tre.2024.103429

Publication date
2024

Document Version
Final published version

Published in
Transportation Research Part E: Logistics and Transportation Review

Transportation Research Part E 183 (2024) 103429

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Handling uncertainty in train timetable rescheduling: A review of the literature and future research directions

Shuguang Zhan [a], Jiemin Xie [b,*], S.C. Wong [c], Yongqiu Zhu [d,e], Francesco Corman [d]

[a] School of Automotive and Transportation Engineering, Hefei University of Technology, Hefei, China
[b] School of Intelligent Systems Engineering, Sun Yat-sen University, Guangzhou, China
[c] Department of Civil Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong
[d] IVT, ETH Zurich, Stefano Franscini Platz 5, 8093 Zurich, Switzerland
[e] Department of Transport and Planning, Delft University of Technology, Delft, the Netherlands

ARTICLE INFO

Keywords:
Railways
Disruption management
Train timetable rescheduling
Stochastic perturbation

ABSTRACT

External and internal factors can cause disturbances or disruptions in daily train operations, leading to deviations from official timetables and passenger delays. As a result, efficient train timetable rescheduling (TTR) methods are necessary to restore disrupted train services. Although TTR has been a popular research topic in recent years, the uncertain characteristics of railways have not been sufficiently addressed. This review first identifies the primary uncertainties of TTR and examines their impacts on both TTR and passenger routing during disturbances or disruptions. It finds that only a few uncertainties have been investigated, and the existing solution methods do not adequately meet practical requirements, such as considering the dynamic nature of disturbances or disruptions, which is crucial for real-world applications. Therefore, the review highlights problems associated with TTR uncertainties that need urgent attention and suggests promising methodologies that could effectively address these issues as future research directions. This review aims to help practitioners develop improved automatic train-dispatching systems with better train-rescheduling performance under disturbances or disruptions compared to current systems.

1. Introduction

Railway transportation has expanded rapidly worldwide in the past several decades owing to its large capacity, punctuality, high comfort and environmental friendliness. Due to this rapid development and increasing rail passenger demand, the density of train operations on railway lines and networks is increasing, resulting in reductions in buffer times and supplements available on lines and networks and thus an increase in the fragility of railway systems. Furthermore, external and internal factors, such as poor weather conditions and the breakdown of railway infrastructure, cause disturbances (small perturbations) and disruptions (large perturbations) of train operations (Xu et al., 2016). According to Cacchiani et al. (2014), a *disturbance* refers to situations where certain railway processes (e.g., train running in a segment or dwell at a station) take longer than the scheduled times in the official timetable, causing train delays. In such cases, typically only train timetable rescheduling is performed without adjusting rolling stock or crew schedules to restore train operations. On the other hand, a *disruption* is a relatively large external incident that significantly affects the train

* Corresponding author.
E-mail address: xiejm28@mail.sysu.edu.cn (J. Xie).

https://doi.org/10.1016/j.tre.2024.103429
Received 8 July 2023; Received in revised form 19 January 2024; Accepted 21 January 2024
Available online 31 January 2024
1366-5545/

timetable, requiring resource duties (e.g., rolling stock and crew) to be rescheduled as well. In scenarios where an unexpected disturbance or disruption occurs, trains cannot run as scheduled, and some may be canceled, leading to passengers experiencing delays or failing to reach their destinations. Railway dispatchers reduce the impact of disturbances and disruptions, caused by unplanned events, on train operations and passenger services. They reschedule trains by different dispatching measures including retiming, reordering, rerouting and/or cancellations. Particularly in railway systems with seat reservations, they may also do the re-assignment of passenger flows, by re-assigning passengers to other operating trains. The impacts of unplanned and planned events on train operations differ significantly, with unplanned events presenting more uncertainties and, consequently, greater challenges to manage. This review concentrates on unplanned events.

Railway rescheduling in response to a disturbance normally only requires timetable rescheduling (TTR); however, rescheduling in response to a serious disruption usually involves not only TTR but also subsequent rolling stock rescheduling and crew rescheduling (Cacchiani et al., 2014). This review focuses on TTR (also called train dispatching) but also considers TTR integrated with other rescheduling processes (e.g., rolling stock rescheduling or crew rescheduling). In the TTR problem, dispatchers need to determine the departure and arrival times of each train at each visited station, the order that trains run in each segment, and which trains need to be cancelled/short-turned, according to the current status of train operations and disruption information. In recent decades, an increasing number of studies have investigated real-time TTR (see surveys, such as those of Cacchiani et al., 2014; Corman & Meng, 2014; Fang et al., 2015; Josyula & Törnquist Krasemann, 2017; Lamorgese et al., 2018; Jusup et al., 2021), but most of these studies have solved the TTR problem in a deterministic way without considering its inherent stochasticity and uncertainty. For example, it has usually been assumed that the duration of a disruption (Zhan et al., 2015; Veelenturf et al., 2016), the running time of a train in a segment (Pellegrini et al., 2014, 2016; Samà et al., 2016, 2017; Zhan et al., 2021, 2022a) or the passenger demand (Zhu and Goverde, 2020; Zhan et al., 2021) in the event of a disruption are known and fixed. In practice, however, the duration of a disruption is normally unknown at the start of the disruption, and train running time and dwell time, and passenger demand, are uncertain.

Expanding TTR to accommodate potential knowledge of these uncertainties is an important objective, as it can lead to significant cost reductions and performance enhancements. Studies have emerged in this research area in recent years but there has been no specific review of the area. It is therefore an opportune time to discuss recent progress on this topic, summarize the lessons learned, and identify research gaps to guide further development of TTR.

As train rescheduling strategies and algorithms for TTR have been extensively reviewed in previous surveys, such as those by Cacchiani et al. (2014), Fang et al. (2015), and Lamorgese et al. (2018), this study does not delve deeply into their general variants. Instead, our review concentrates on the uncertainties associated with TTR, the existing approaches for solving TTR with uncertainty, the research gaps, and potential methods to address TTR with uncertainty.

This review contributes to research on the TTR problem by

- synthesizing the literature on real-time TTR, with consideration of its stochastic and uncertain conditions;
- analyzing potential uncertainties involved in real-time TTR that must be considered in railway practice;
- systematically classifying the state-of-the-art approaches for managing uncertainty in real-time TTR and discussing their advantages and disadvantages; and
- identifying research gaps in the literature and proposing future directions for research.

This review is expected to help researchers address the real-time TTR problem under uncertainty, become familiar with state-of-the-art methodologies, understand the research agenda and conduct new research on TTR; and to help railway practitioners to recognize the impact of uncertainty on real-time TTR and guide their future railway planning and dispatching.

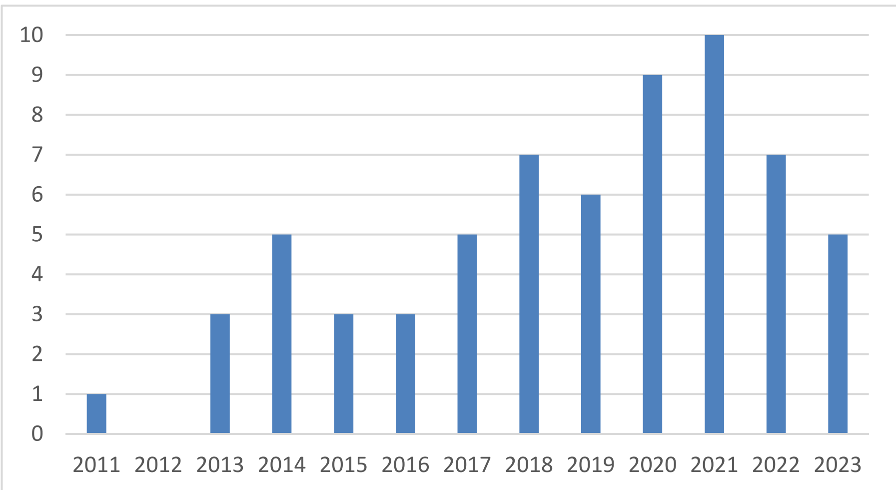

Fig. 1. Distribution of selected papers per year.

The remainder of this paper is organized as follows. Section 2 provides the background and outlines the problem setting. Section 3 classifies the uncertainties involved in TTR practice and analyzes the impacts of these uncertainties on TTR. Section 4 comprehensively reviews selected studies on various types of uncertainty and solution approaches. Section 5 comprises discussions and suggested directions for future research. Section 6 contains the conclusions.

2. Methodology for literature review

To provide a comprehensive overview of the state-of-the-art research on TTR with uncertainty, we conducted a thorough search of papers in two primary databases: Google Scholar as the main source and Web of Science as a supplementary source. Our search included all relevant papers published before April 2023. We employed various keywords such as "uncertain train rescheduling/ dispatching," "stochastic/robust train rescheduling/dispatching," "uncertain demand & train rescheduling/ dispatching," "uncertain information & train rescheduling/dispatching," and "predict railway disruption" in the title, abstract, and keywords. We limited our scope to academic journals and conference proceedings written in English. Our search process involved four steps. First, we initially selected papers closely related to our research topic based on each mentioned keyword. Second, we then excluded papers focusing on train timetabling, those addressing rescheduling of rolling stock and/or crew, and those discussing TTR without considering uncertainty. Third, we employed a forward snowball method to identify relevant papers from the references of the selected studies. Finally, we carefully examined the full texts of all the searched papers, removing any irrelevant ones and categorizing the remaining ones. Following this process, we ultimately reviewed 65 papers.

Fig. 1 displays the annual number of publications. It is evident that prior to 2013, TTR with uncertainty had garnered minimal attention. However, over the past decade, this topic has emerged as a prominent research area, attracting substantial interest.

3. Background and problem setting

Railways are based on the organization of very expensive and limited resources (e.g., vehicles and infrastructure), which are planned very well to make sure they are well utilized. This strong planning conflicts with the fact that operating conditions change all the time and are uncertain and/or not known perfectly, at some moments in time.

We term uncertainty aware approaches those that are able to consider such uncertainty in some aspects of their mathematical modeling or solution finding. Those approaches fit in the broad arena of sequential decision making, and have been termed and defined in various ways, including keywords such as robust, reliable, and stochastic which have been sometimes conflicting or unclear. We, therefore, distinguish processes, which are partially controllable and controlled, from uncertainty which we assume depends on exogenous aspects, which are not controllable, and which result in a realization at some moment in time. We distinguish between a nominal plan and an actual plan, which depends on the specific exogenous aspect. The mathematical models are targeted to determine the best value of the decision variables, such that the actual outcomes are achieving the best system performance. A timetable that is obtained based on incorrect assumptions, for instance assuming a deterministic perfectly known behavior of the system might be infeasible or not optimal in practice, due to the existence of uncertainties, and the effect of the exogenous aspects.

Due to the regular offering of railways, we assume statistical data about the past could describe the process. In fact, the big interest in uncertainty aware approaches stems from the large amount of data collected in the past, which gives hopes to use this data to improve operations. This data shows a large amount of variations, and functional relations between processes and decision variables.

One possible way to address this uncertainty is to be *reactive*, i.e., every time an exogenous aspect occurs, and a realization happens, the operating plan is adjusted. *Proactive* approaches have to do with a characterization of the process realization expected value and/or uncertainty, ahead of time. Accurate prediction of the involved uncertainties based on the limited future information is critical and difficult, and a bad prediction has a serious influence on the quality of TTR or even causes the obtained solution infeasible. Many rules of thumb have been determined to address this fundamental problem of planning under uncertainty. For instance, one can refer to the worst case, or confident estimates. The obtained solution of TTR can be too conservative and the quality of the solution tends to be low. On the other hand, if the uncertainties are not fully considered, the obtained solution may be infeasible. Including predictions which are not just point-estimates, but full distributions, lends itself to potential improvements of quality and feasibility of obtained solutions. The methods required to do so, though, are complex and scale badly with the characterization of uncertainty (scenarios, number of exogenous factors modeled) and decision variables (traffic, level of detail). Therefore, there might be impacts on the resulting solution quality.

Overall, the state-of-the art seems approaches which deal with uncertainty ("The concept or condition of being in doubt about a value": Tumeo, 1994). Some of them are able to model the uncertainty by some probability distributions, and are often termed stochastic approaches ("Random variations of processes over time and space, the magnitude, frequency, duration and/or other characteristics of which can be described by theories of probability": Tumeo, 1994).

In fact, a factor might be considered as noise (uncertain), as a probability distribution (stochastic) or as an input to the problem (reactive). This depends on the information available and exploited at the time the decision process is solved. Some factors are uncertain in nature, but can be well characterized by probability distributions, especially if they are relatively common. Some events are rare, and the definition of their occurrence is subject to uncertainty and modeling errors. Apart from special cases, future states of the system cannot be known with certainty, and the determined planning can be designed based on the uncertain/incomplete description of the system at that moment. However, when more information is available with time going on, a better action can be taken based on the newly received information. For example, whether a disruption will occur is uncertain before it really occurs in TTR problems; however, at the moment a disruption occurs, we know that it really happens, but the duration of the disruption is still uncertain and usually modeled by stochastic programming. Other aspects, such as delays might still be uncertain.

Robustness is also a concept which is often used. In this review, we distinguish two types of robustness: *solution robustness* and *model robustness*. Solution robustness implies that the *actual* solution has good performances, concerning all exogenous aspects of the processes. In other words, the solution is “nearly” optimal in terms of quality, considering the potential realizations of the uncertain parameters, as assessed from the quality perspective. In contrast, model robustness means that the *nominal* solution has the property to translate naturally in the *actual* solution. In other words, the solution is “nearly” feasible in all possible realizations of uncertain parameters. Model robustness is a distinct branch of operations research (Govindan et al., 2017). Many existing studies have employed robustness without explicitly focusing on either of the two concepts, leading to confusion among readers (e.g., Li et al., 2015; Moaveni & Najafi, 2017; Xu & Ng, 2020). In this review, the term “robust” in, e.g., robust timetable and robust disposition timetable, refers to solution robustness. Meanwhile, the term “robust” in, e.g., robust model and robust optimization, refers to model robustness.

4. Classification and impacts of uncertainties involved in TTR

Trains are expected to operate according to an official timetable, making the train operation system a schedule-based system. A well-designed official timetable ensures the punctuality of daily train operations. However, a railway system is dynamic and fragile, and train operations can be easily affected by external and internal factors, as mentioned above. Railway dispatchers or managers can implement various measures to manage trains and rearrange passengers when unplanned events occur due to external and internal factors. Ignoring these unplanned events may lead to deadlocks or even accidents, putting both trains and passengers in danger. Alternatively, emergency responses can be employed to handle trains and delayed passengers. While railway staff may be busier due to these reactive measures, the impact of events on both train operations and passenger services is reduced. The impact of unplanned events can be mitigated if contingency plans are made in advance. For example, incorporating additional buffer times and supplements into the official timetable or conducting more frequent and rigorous inspections and maintenance on railway infrastructure can be beneficial. However, excessive measures can lower the efficiency of train operations and passenger travel while increasing costs for train operation companies.

In a busy railway system, the delay of one train may affect several following trains, and a train delay on one line tends to propagate to other connected lines; this is known as a snowball effect. It is therefore challenging for train dispatchers to reschedule trains in such a complex system following a disturbance or disruption, especially given the uncertainties involved in train operations. These uncertainties are classified according to railway operation practice, and we analyze their impacts on TTR in the following passages and

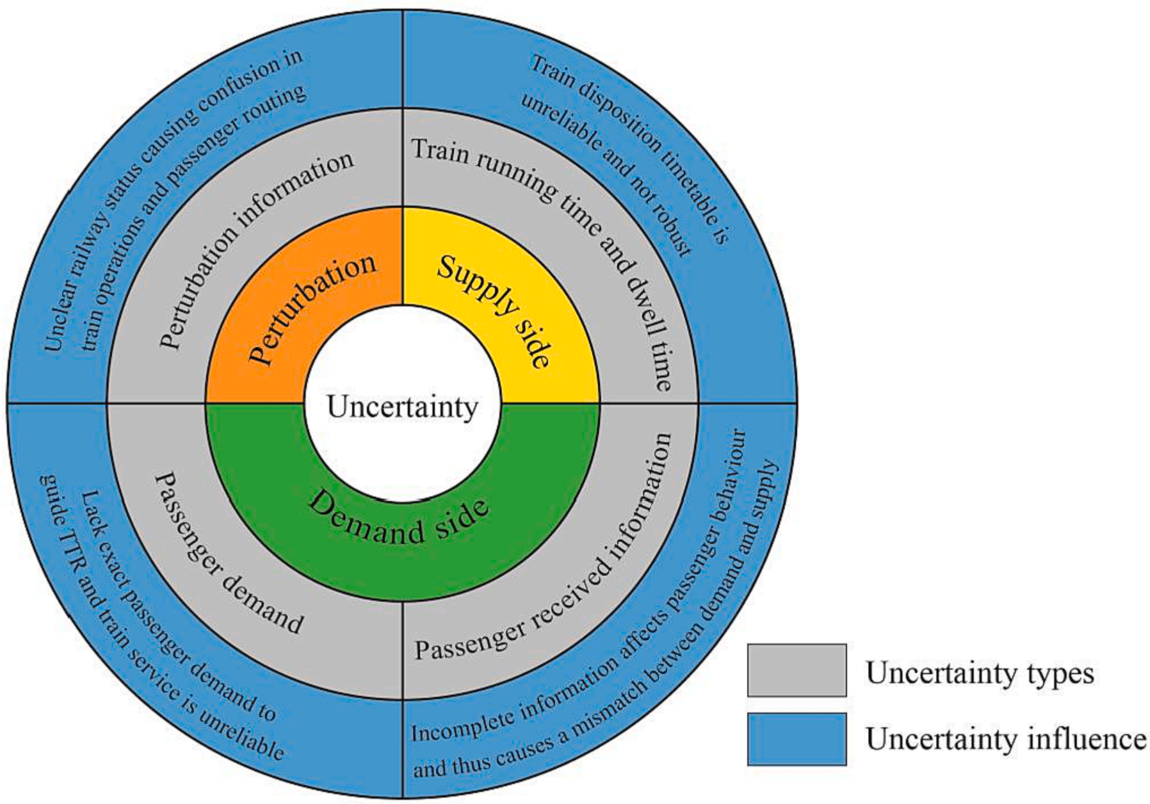

Fig. 2. Various types of uncertainties and their impacts on TTR.

present general information on uncertainties in TTR in Fig. 2. In this review, the primary focus is placed on TTR rather than rolling stock or crew rescheduling. The distinction between disturbances and disruptions is not the main emphasis of this review (for details, please refer to Cacchiani et al. (2014)), although their impacts on the railway system may vary. Instead, the term "perturbation" is used to encompass both situations.

The exogenous aspects resulting in uncertainties involved in the TTR problem can be traced from three aspects: perturbation, supply side and demand side. From these three aspects, four types of uncertainties are analyzed in the following subsections 4.1 to 4.4 respectively, including uncertain perturbation information, uncertain train running time and dwell time from supply side, uncertain passenger demand and passenger received information from demand side.

First, the information regarding the perturbation itself is usually uncertain. The uncertainty lies in the occurrence, status change, and duration of a perturbation. Second, uncertainties exist in the actual running times and dwell times of trains, which can differ from the scheduled ones. This type of uncertainty is somewhat correlated with the uncertainty in perturbation. For example, a train may have an additional stop at a station (i.e., increased dwell time), which serves as the entrance to a segment blocked due to a sudden perturbation. Third, the information provided to passengers during a perturbation can be incomplete, while passenger behavior is influenced by the information received. This creates difficulty in accurately estimating passengers' route choices and, consequently, the demand. During a perturbation, the inflow demand can differ significantly from the usual, due to lower service frequency, quality, and reliability. It is challenging to estimate how many passengers will remain in the railway systems during a perturbation, although this estimation is crucial for guiding TTR.

To handle the uncertainties involved in TTR, information collection and prediction are usually made before optimization. It should be noted that all the mentioned uncertainties are significantly affected by the time when the uncertain information is collected or predicted. As discussed by Büchel & Corman (2022), the predictability is improved as the event to be predicted gets closer in time. That is, the predicted variability is reduced as time goes on, as more new information becomes available.

4.1. Uncertain perturbation information

Perturbations comprise planned perturbations, such as programmed railway maintenance, and unplanned perturbations, i.e., sudden occurrences. Planned perturbations are known to railway dispatchers, which enables them to reschedule trains in advance to minimize delays. In contrast, unplanned perturbations occur unexpectedly (e.g., a sudden rolling stock breakdown or a railway line blockage), so dispatchers must manage trains in real-time according to the up-to-date perturbation information (e.g., a perturbation's occurrence time, location, and estimated duration) after the perturbation has occurred. It is challenging for dispatchers to effectively reschedule trains without any preparation, especially when perturbation information lacks accuracy and undergoes dynamic changes and updates, which is typically the case. This review focuses on unplanned perturbations.

Inaccurate and dynamic perturbation information is mainly information on the uncertain duration of a perturbation and the dynamic changes of a perturbation. It is obvious that railway dispatchers do not know how long a perturbation will last at the beginning of the perturbation. In railway practice, dispatchers reschedule trains according to an estimated duration, which is based on their experience and that of maintenance staff. However, there are at least two drawbacks to this rescheduling strategy. First, an estimated perturbation duration is strongly reliant on railway staff's experience and may substantially deviate from the real duration. The quality of TTR is negatively affected by both an optimistic estimation of perturbation duration (i.e., an estimated duration that is shorter than the real duration) and a pessimistic estimation of perturbation duration (i.e., an estimated duration that is longer than the real duration) (Zhan et al., 2016). Second, a duration estimation is updated as perturbation recovery continues, meaning that TTR must be re-performed. This repeated rescheduling of trains may be time-consuming and confuse railway staff for implementation. Moreover, dynamic changes in perturbation mean that perturbation status may change throughout a disruption period. For example, a perturbation may initially completely block a segment, but subsequent rescue work may partly open the segment and thereby allow trains to pass at a lower speed than normal. However, at the beginning of a perturbation, it is unknown when and how such dynamic changes in perturbation status will occur, which increases the difficulty of TTR. Until now, dynamic changes in perturbation have not been given much attention by railway researchers investigating the real-time TTR problem (although closed-loop approaches mentioned in Corman & Meng (2014) and Van Thielen et al., (2018, 2019) were partly used to handle them). This is one of the main reasons why most TTR solutions cannot be implemented in real-world train-dispatching systems (Schön & König, 2018; Jusup et al., 2021).

4.2. Uncertain train running time and dwell time

For technical reasons, a train has a minimum running time requirement in a segment and a minimum dwell time requirement at a station; however, its scheduled running time and dwell time, which are presented in an official timetable, are usually longer than these minimum requirements. The difference between the scheduled and the minimum required running or dwell time is usually referred to as the supplement. The supplement can be utilized to address uncertain train running (e.g., due to driver behavior) and excessive passenger boarding and alighting in daily train operations. That is, supplements are incorporated into an official timetable, such that a normal train schedule is robust against small perturbations, and the punctuality of trains is high. However, in the event of a large perturbation that seriously affects trains, the exact running time in a segment and dwell time at a station are uncertain. This is because the actual running time of a train depends on the perturbation status, driver behaviors, and the number of onboard passengers, whereas the dwell time is strongly affected by the number of boarding and alighting passengers.

Most studies have ensured only that the running time and dwell time are not smaller than the minimum required times in their TTR models (see studies covered in the surveys by Cacchiani et al., 2014; Corman & Meng, 2014; Fang et al., 2015). In these cases, trains run as fast as possible with small dwell times to minimize the total train delay in the disposition timetable, but the obtained disposition timetable is not robust without the incorporation of sufficient supplements. Therefore, any perturbation of the running time or dwell time may make the disposition timetable infeasible, such that it cannot be implemented in practice (Reynolds & Maher, 2022). In addition, some recent TTR studies have treated the running time and dwell time as given and fixed values (which may be longer than the minimum values) because performing TTR in a time–space network-based model with specific given running times and dwell times is easier than in variable models (Zhan et al., 2021, 2022a). However, determining a proper given running time and dwell time that considers real-world dynamics (e.g., the real-time driver behavior and passenger boarding and alighting processes) is not easy, and this strongly affects both the quality and robustness of a disposition timetable.

4.3. Uncertain passenger demand

The primary objective of a passenger railway transportation system is to optimize its services to enhance passenger convenience while maintaining manageable train operation costs. This means that the train operation supply in such a system should well match the real passenger demand, so determining the exact passenger demand is the basis of passenger-oriented train scheduling (Parbo et al., 2016) and rescheduling (Josyula & Törnquist Krasemann, 2017; Sharma et al., 2023). The forecasting of passenger demand on a normal day has drawn much attention in the field of train scheduling, but the behavior of passengers during a perturbation is different from that on normal days (Leng & Corman, 2020). Once a perturbation occurs, especially if it is a large incident that blocks train operations for a relatively long period (e.g., the blockages that have been considered in Zhan et al., 2015, 2016; Zhang et al., 2023), some trains suffer a large delay and others are cancelled. Therefore, passengers on delayed or cancelled trains might be transferred to other trains that can transport them to the destinations with less delay, and some passengers might decide not to travel by train. Passengers' behavioral changes are influenced by the perturbation situation, the disposition timetable, and passenger features such as age, income, and travel purpose (Currie & Muir, 2017; Adelé et al., 2019; Mo et al., 2022). Therefore, passengers' behavior during a perturbation is difficult to predict, so real-time passenger demand is uncertain and difficult to determine.

Most previous studies on TTR have been train-oriented instead of passenger-oriented; i.e., the objective of TTR has been to minimize the impact of perturbations on train operations instead of on passengers (Josyula & Törnquist Krasemann, 2017). In this case, an obtained disposition timetable tends to be inconvenient for passengers. The few studies that have considered passenger demand have assumed that the total demand remains unaffected by a perturbation. However, passengers' route choices on the considered railway network may change, and some passengers may abandon train travel if their travel costs exceed a certain value (Binder et al., 2017, 2021; Zhu & Goverde, 2020a; Zhan et al., 2021). Although switching to other transport modes is allowed (Borecka & Bešinović, 2021), heterogeneous passengers tend to have different preferences due to their travel purposes or available alternatives. As a result, the actual passenger demand after a perturbation is not obtained. In this situation, a disposition timetable may not align with the actual passenger demand, leading to wasted train capacity and a decrease in passenger service quality.

4.4. Uncertainty in which information received and considered by passengers

In railway practice, information on a perturbation and the disposition timetable or traffic control strategies are not exactly known by all affected passengers, because there is no medium by which messages can be sent to all passengers in a timely manner, and because passengers may not check current information that they have received (Leng & Corman, 2022). For example, although sending messages to mobile phones is considered as a useful method for timely message delivery, not all railway passengers possess a mobile phone, and it is not guaranteed that each passenger will check their mobile phone once receiving a message. Furthermore, some messages are available onboard, while others can only be accessed at stations (Zhu & Goverde, 2019). Therefore, the information of which a passenger is aware may be incomplete and not up to date. In addition, even if passengers receive perfect information, such as the best recommended route, they may not fully follow the recommendation. For example, a railway manager tends to recommend alternatives to each passenger from a system-optimal perspective, but a passenger may have their own preference and pursue their own best (user optimal) profit. Consequently, it is uncertain whether a passenger will comply a given suggestion (Van der Hurk et al., 2018).

On the one hand, the amount of information received by passengers substantially affects their choice behavior in the event of a perturbation (Leng & Corman, 2022) and thus may cause congestion and reduce the quality of TTR. On the other hand, the number of passengers who follow recommended alternatives affects real-time passenger demand. As each train has a limited capacity, whether passenger demand is fulfilled depends on whether passengers follow the recommendations, and this affects TTR.

5. Existing approaches for managing TTR under uncertainty

Methodologies for managing TTR have been extensively reviewed by, for example, Corman & Meng (2014) and Fang et al. (2015) from a model-driven perspective and Wen et al. (2019) and Jusup et al. (2021) from a data-driven perspective. Corman & Meng (2014) mentioned that a closed-loop control showed promise in managing uncertain perturbation status, and it is suggested by Wen et al. (2019) that a large number of train operation records could be applied to learn train rescheduling rules while considering part of the real-world dynamics of train operation processes. However, uncertainties have not been a main consideration in these reviews. Thus, the present review concentrates on the TTR problem under uncertainty. As described in Section 4, at least four types of uncertainties are involved in this problem and they have different effects on train operations and passenger services. Consequently, studies that have developed approaches for managing these four types of uncertainties have been reviewed. The existing research questions and solution approaches for TTR under uncertainty are depicted in Fig. 3.

As illustrated in Fig. 3, some solution approaches, such as stochastic programming and data-driven approaches, have been employed to address multiple types of uncertainties. In contrast, other approaches, like the rolling horizon approach and discrete choice modeling, have only been used to tackle specific types of uncertainties. This is because certain approaches are suitable for managing uncertainties with particular characteristics. For example, the rolling horizon approach is well-suited for problems where uncertain information remains constant for a period and is updated later on. Meanwhile, other approaches may not be as effective in exploiting specific assumptions and may yield less optimal results, but they can be applicable to a broader range of solutions. To make informed decisions on handling uncertainty in TTR, it is crucial to understand the uncertainty behavior of the process and the ultimate goal of the optimization. These factors should influence the choice of approach for addressing uncertainty.

5.1. TTR with uncertain perturbation information

Uncertain perturbation information strongly affects TTR. Normally, uncertainty is related to the occurrence time and location, duration, and possible status changes of a perturbation. In this subsection, studies on TTR under uncertain perturbation information are reviewed in terms of the approaches they have taken (see Table 1).

(1) Rolling horizon approach

In railway practice, the information on a perturbation is updated over time; for example, only limited or predicted information is initially available, and more information is received in a stepwise fashion from railway managers or maintenance staff. In addition, railway dispatchers usually reschedule trains stage by stage instead of rescheduling all of the trains for a whole day at once; e.g., a stage plan for Chinese railways covers train operations for only the following 3 or 4 h. Motivated by these experiences from railway practice, the *rolling horizon approach* (RHA) or *model predictive control* (MPC) (classified as closed-loop control by Corman & Meng, 2014) has been adopted to manage the uncertain duration of a perturbation. The RHA is essentially a deterministic approach, but it is solved in a rolling horizon framework which is the same as MPC in control theory. In an RHA (see a general procedure for k stages in Fig. 4), the whole TTR period (e.g., 1 day) is divided into several planning periods and roll periods. In each stage, only train operations in a planning period (p) are rescheduled, whereas the obtained disposition timetable for a roll period (r) is implemented by railway dispatchers, and those beyond the roll period (i.e., look ahead period l) are rescheduled again in the following stage. Thus, the fundamental principle of RHA is to iteratively solve a deterministic TTR problem while taking into account updated perturbation information. In RHA, a new optimization iteration typically occurs after a roll period. However, it may also be initiated earlier due to updates in perturbation information. For example, in Fig. 4, stage 3 commences at time t_3, which is not a roll period after the start time (t_2) of previous stage 2.

To the best of our knowledge, Meng & Zhou (2011) were the first to adopt the RHA to manage the uncertain duration of a perturbation in a single-track railway TTR problem. Zhan et al. (2016) rescheduled trains for a partial segment blockage on a double-track high-speed railway line where the duration of the blockage was uncertain and used the RHA to manage the uncertainty. RHA was also utilized in Peng et al. (2023) to solve TTR and train-speed management under temporary speed restrictions, in order to handle the uncertainty of segment speed restrictions. As a predicted perturbation duration is still required for each stage of the RHA, the prediction accuracy affects the solution quality (Cavone et al., 2017). It was suggested that a pessimistic estimation is preferable to an optimistic estimation for ensuring the feasibility and quality of a whole train-disposition timetable when the exact estimation is unavailable (Zhan et al., 2016).

To further manage the uncertainty of a perturbation prediction for each stage in the RHA, a stochastic approach has been used,

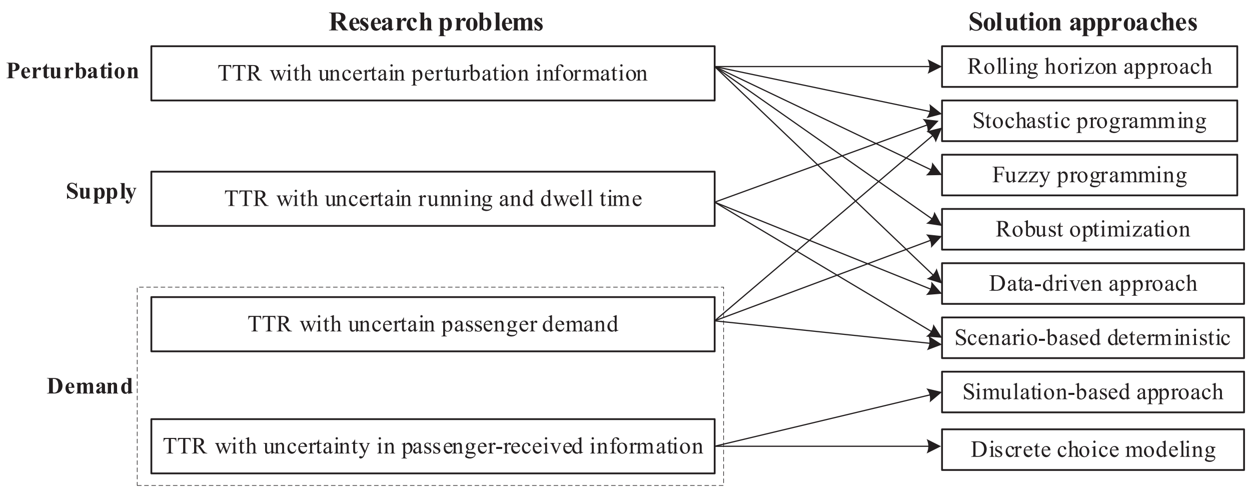

Fig. 3. Existing research problems and involved solution approaches.

Table 1
Studies on TTR with uncertain perturbation information.

Uncertainty	Approach	Detailed strategy	References
Perturbation information	Rolling horizon	Update the train timetable stage by stage in a deterministic manner when new perturbation information becomes available	Meng and Zhou (2011), Quaglietta et al. (2013), Zhan et al. (2016), Cavone et al. (2017), Corman et al. (2018), Zhu and Goverde (2020), Peng et al. (2023)
	Stochastic programming	Optimize the train timetable under various perturbation scenarios with known probabilities	Meng and Zhou (2011), Li et al. (2014), Meng et al. (2016), Zhu and Goverde (2020), Hong et al. (2021), Liu et al. (2022)
	Fuzzy programming	Optimize the train timetable under various perturbation durations with a fuzzy member function	Yang et al., (2013, 2014)
	Robust optimization	Optimize the train timetable with an uncertainty set of perturbations	Xu and Ng (2020), Xu et al. (2021)
	Data-driven approach	Optimize the train timetable using perturbations predicted from historical data	Fink et al., (2013, 2015), Zilko et al. (2016), Ghaemi et al. (2018), Schön and König (2018), Yap et al. (2019), Grandhi et al. (2021)

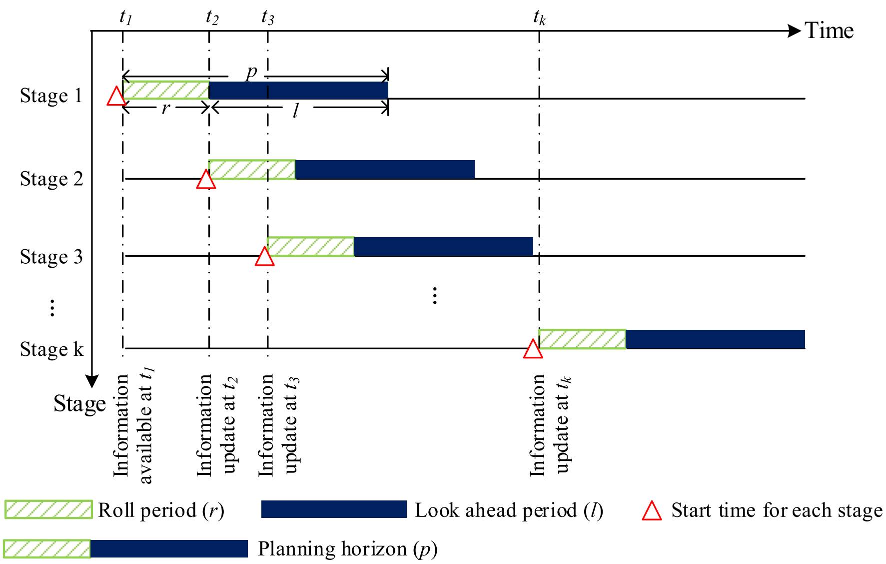

Fig. 4. Procedure for a general rolling horizon approach.

whereby the duration of a perturbation is assumed to be represented by several scenarios with given probabilities instead of having a fixed value (Meng & Zhou, 2011; Zhu and Goverde, 2020). The inclusion of the two-stage stochastic programming in an RHA can be regarded as a multi-stage stochastic programming, but it is solved in a rolling horizon framework. The solution quality is improved, but the solving process is complicated due to the generally large number of scenarios. Furthermore, the robustness of the schedule can be incorporated into the RHA by establishing a deterministic multi-objective mixed-integer programming model that aims to minimize train deviation (delay) while simultaneously maximizing the schedule's robustness (Cavone et al., 2017).

Although the RHA is easily implemented, its solution quality is affected by the length of the planning period (p in Fig. 4). A longer planning period tends to have better solution quality (in terms of total train delays) but usually at the cost of longer computational time (Zhan et al., 2016). However, the dynamic nature of a perturbation means that a long planning period in the RHA may not lead to a stable solution. In this context, a stable timetable is defined as one in which any train delay can be absorbed by supplements and buffers in the timetable without the need for rescheduling (Goverde & Hansen, 2013). Therefore, a longer planning period is not necessarily better than a shorter planning period (in terms of stability), so the length of a planning period needs to be carefully determined (Quaglietta et al., 2013; Corman et al., 2018).

(2) Stochastic programming approach

As mentioned above, the actual duration of a perturbation varies and it can be regarded as a series of intervals (i.e., scenarios). Therefore, a scenario-based stochastic programming approach can be applied to model the TTR problem with an uncertain perturbation duration. A general stochastic programming model for TTR with uncertain perturbation information is expressed as follows

$$\min \sum_{\omega \in \Omega} p_\omega f(x, d_\omega) \tag{1a}$$

$$\text{s.t.}\, x \in Z_\omega, \forall \omega \in \Omega \tag{1b}$$

where $\omega \in \Omega$ represents a perturbation scenario, Ω is the set of perturbation scenarios, p_ω denotes the probability of scenario ω, and $f(x, d_\omega)$ signifies the cost of train rescheduling under scenario ω (d_ω indicates the occurrence of perturbation scenario ω). Z_ω is defined as the constraint set for decision variables x under scenario ω. The objective function represents the expected cost of train rescheduling across all possible perturbation scenarios.

In contrast to the above-mentioned RHA, in which a deterministic perturbation duration is used in each computational stage, stochastic programming assumes that there are multiple possible perturbation durations in each stage (i.e., various scenarios in set Ω). Determining the scenario set Ω and the probability of each scenario p_ω is a critical problem and various ways have been devised to determine them in previous studies. Li et al. (2014) treated the uncertain duration of a disruption with a density function and assumed that the density function was known a priori. In stochastic programming, owing to the uncertain duration of a perturbation, the perturbation is usually regarded as comprising various scenarios with known probabilities (Meng et al., 2016; Hong et al., 2021; Liu et al., 2023). Compared with a disposition timetable generated by rescheduling trains in a deterministic way, a disposition timetable generated by rescheduling trains in a stochastic environment (i.e., considering various scenarios) is more robust, but it needs to be updated when different perturbation scenarios (e.g., disruptions with different durations) are fulfilled. Frequent updating (i.e., adjustment) of a disposition timetable may confuse railway staff and passengers, as they do not know which timetable to follow at a given moment. To overcome this difficulty, some decisions are not allowed to be changed in various perturbation scenarios. For example, train routing was fixed by Meng et al. (2016), and a train stop plan was fixed by Hong et al. (2021) for various disposition timetables obtained in different scenarios. Both Meng et al. (2016) and Hong et al. (2021) argued that the robustness of a disposition timetable was increased by fixing certain components when rescheduling trains, because the obtained disposition timetable does not need to be substantially updated; only a slight adjustment is needed to meet the requirements of a specific perturbation scenario.

Recently, two-stage stochastic programming, which is a special case of stochastic programming, was applied to solve the TTR problem under uncertain perturbation durations, where the first-stage optimization was independent of the uncertain duration and this uncertainty was only involved in the second-stage problem. Therefore, a deterministic decision was involved in the first stage, and a recourse function was involved in the second stage. The compact form of a linear two-stage stochastic programming can be expressed as follows (Birge & Louveaux, 1997)

$$\min c^T x + E[Q(x, \omega)] \;\; \text{s.t.}\, Ax = b,\, x \geq 0 \tag{2a}$$

where

$$Q(x, \omega) = \min\{qy(\omega) | Wy(\omega) = h - Tx, y(\omega) \geq 0\} \tag{2b}$$

In model (2a)-(2b), the first-stage decision variable is represented by x, and the second-stage decision variable related to random vector ω is represented by $y(\omega)$. Vectors b, c, q and h, as well as matrices A, W, T are also included in the model. The cost corresponding to the first-stage variable x and the expected value of recourse cost on the second-stage variable $y(\omega)$ are minimized in the objective function. A specific random vector ω can be considered as a scenario, and each scenario $\omega \in \Omega$ is associated with a probability p_ω similar to that in model (1(a)-1(b)). In the case of a TTR problem with uncertainty, the first stage involves determining the rescheduling decisions x (e.g., delaying or cancelling trains) that remain consistent across all perturbation scenarios. The second stage entails deciding on the scenario-based rescheduling decisions y(ω), which may vary across scenarios. The objective function in (2a) aims to minimize the rescheduling cost (e.g., measured in train delays and cancellations) of the first-stage decisions, in addition to the expected rescheduling costs of the second-stage decisions for all perturbation scenarios. The first-stage and second-stage decisions can be defined in various ways. For instance, determining train orders at the first stage, which will remain fixed in the second stage when deciding train departure and arrival times, can differ across perturbation scenarios. Constraints in (2a) typically encompass train running and dwell time constraints, headway and station capacity constraints, as well as constraints related to the perturbations. For more information about TTR constraints, please refer to sources such as Zhan et al. (2015).

Meng & Zhou (2011) and Zhu and Goverde (2020) have embedded the two-stage stochastic programming approach into the RHA to improve the robustness of the obtained disposition timetable. Differing from a deterministic RHA, where a deterministic model was utilized for each stage of an RHA, a two-stage stochastic model was employed for each stage problem of an RHA, which could be considered as a multi-stage stochastic programming (Zhu and Goverde, 2020). A two-stage stochastic approach was also used by Liu et al. (2022) to manage an uncertain blockage, where the first stage dealt with the TTR before the minimum end-time of the perturbation (i.e., independently of the actual perturbation length), and the second stage rescheduled trains with consideration of potential longer perturbations than those considered in the first stage (i.e., depending on the uncertain duration).

However, although stochastic programming can help to improve the robustness of an obtained disposition timetable, it assumes that the probability of each perturbation scenario (p_w in Eq. (1a)) is known a priori. This is not true in practice, because the exact probability is unknown, so how to determine the exact probability is worthy of further study. In addition, the number of scenarios chosen in two-stage stochastic programming (i.e., the number of elements in set Ω for scenarios ω in model (2a-2b)) affects the computational time and the solution quality. Therefore, it is critical to select an appropriate number of scenarios, and this aspect also requires further investigation. To overcome the computational complexity of multiple scenarios, sample average approximation (Shakibayifar et al., 2017) and decomposition approaches such as Benders' decomposition (Bortolomiol et al., 2021) and Lagrangian relaxation (Meng et al., 2016) have been applied to decompose multi-scenario problems into single-scenario problems.

(3) Fuzzy programming approach

To fully exploit the experience of railway staff, an uncertain perturbation duration has been modeled using a fuzzy variable (Yang et al., 2013, 2014). Yang et al. (2013) contended that the possible recovery time could be estimated as fuzzy information by professional judgments rather than discrete random variables (e.g., scenarios in stochastic programming). A two-stage fuzzy mixed-integer programming was formulated for the TTR problem, where the train orders in each segment were determined in the first stage based on fuzzy perturbation durations (perturbation scenarios), and the detailed train schedule was determined in the second stage to evaluate the solution quality, based on the train orders obtained in the first stage. In subsequent research (Yang et al., 2014), a credibility-based two-stage fuzzy 0–1 integer optimization model was employed to enhance the reliability of the disposition timetable. As the number of fuzzy values (scenarios) influences the solution space, the model of Yang et al. (2014) proved difficult to solve for large cases using general algebraic modeling system software.

(4) Robust optimization approach

A robust optimization approach has recently been adopted to solve the TTR problem under uncertainty (mainly for metro systems instead of mainline railways) to overcome the difficulty of obtaining the exact probability required by stochastic programming. Considering that unanticipated perturbations such as a station platform breakdown may occur in a metro system, Xu & Ng (2020) introduced a two-stage (i.e., operation-as-usual stage and disruption stage) robust optimization approach to mitigate the impact of uncertain perturbations on passengers. They constructed an uncertainty set to model the uncertain perturbation instead of scenarios with known probability (as done in stochastic programming) and applied a min–max optimization approach to improve the performance of the worst-case perturbation scenario. A two-stage robust optimization model (Xu & Ng, 2020) is expressed as

$$\min \sum_{k \in K} \theta_k \max_{\delta_k \in \Theta_k} f_k(x,\ S_{k-1}(x),\ \delta_k) \tag{3a}$$

$$\text{s.t. } x \in \mathrm{X} \tag{3b}$$

$$(S_1(x), \cdots, S_T(x)) \in \mathscr{R} \tag{3c}$$

where the objective is a min–max function that minimizes the weighted sum of the worst-case impacts of various perturbation scenarios. Function f_k quantifies the impact of a perturbation that occurs at time k in the disruption stage and is a function of the operation-as-usual-stage pre-emptive controls x that are implemented, $S_{k-1}(x)$ is the system state immediately before the beginning of the perturbation (i.e., at time k), and $\delta_k \in \Theta_k$ is a scenario of the train status after time k. Here, Θ_k is the possible set of train-status resulting from a perturbation that occurs at time k because perturbations are uncertain. Parameter θ_k is the weight for a perturbation that occurs at time k, which can differentiate the magnitude of perturbation impacts occurring at different times. Constraint (3b) requires that the train operation state x be within the feasible set X, and constraint (3c) ensures that the trajectory of passengers is within the set of feasible system state trajectories ($\mathscr{R}$). The operation-as-usual stage is designed to model the system state $S_i(x)$ for each $i \in T$ (T is the end of planning horizon) under pre-emptive control x, while the disruption stage aims to evaluate the impacts of various disruption events. For more details of the compact model (3a–3c), please refer to Xu & Ng (2020).

In a subsequent study, Xu et al. (2021) optimized the tolerance (i.e., uncertain disruptions can be tolerated by rail service operations while meeting acceptable service levels) of a metro system with consideration of uncertain perturbation location and duration. They adopted a distributionally robust optimization approach to maximize the minimum-expected downtime that rail transit networks can tolerate over an ambiguity set of random perturbations. As the introduced distributionally robust optimization model is difficult to solve, it has been translated to a mixed-integer linear programming model that can be solved using commercial solvers, such as CPLEX.

The robust optimization approach has been extensively utilized for managing uncertainty in various research areas (García and Peña, 2018), although its application to handling uncertainty in TTR remains in the early stages. The selection of an appropriate uncertainty set is crucial for solving a robust problem and ensuring the quality of its solution. Several robustness models exist, such as strict robustness, adjustable robustness, and light robustness. As the distinction between different robustness models and their applications is not the primary focus of this review, we direct interested readers to the book by García and Peña (2018).

(5) Data-driven approach

As mentioned above, TTR with uncertain perturbation information can be managed by adopting a scenario-based RHA, stochastic programming and robust optimization. However, a proper scenario set is required in the RHA or stochastic programming or an ambiguity set is required in robust optimization, and these requirements affect the final solution quality and computational time. Therefore, it is a critical and challenging task to correctly determine these scenario and ambiguity sets. Data-driven approaches can be applied for estimating uncertain perturbation information based on historical data and can contribute to an improvement in the accuracy of building a scenario or ambiguity set. Upon predicting uncertain perturbation information using data-driven methods, TTR algorithms can be more effectively integrated with the predicted information to address the problem. Zilko et al. (2016) modeled railway perturbation lengths using copula Bayesian networks and tested their approach on track circuit perturbations in the Dutch Railways network. Their results showed that the prediction of the perturbation length was sound and fast, and could potentially be used by Dutch Operational Control Center Rail. Their approach for perturbation length prediction was implemented in TTR in response to a complete blockage to investigate the impact of perturbations on passengers (Ghaemi et al., 2018). More recently, machine learning models have been used to predict perturbation duration and analyze the relationship between perturbation duration and delay on the Danish Railways network (Grandhi et al., 2021). Rather than solely relying on data-driven approaches to predict uncertain perturbation information, Liao et al. (2020) directly solved the metro TTR problem with uncertain train dwell time disturbances using deep learning techniques, specifically a Modified Genetic Algorithm-Gate Recurrent Unit.

In addition to predicting the duration of a perturbation, predicting the occurrence of a perturbation contributes to TTR. Most studies have modeled TTR based on the assumption that the occurrence of a perturbation cannot be anticipated (Zhan et al., 2015, 2021; Zhu & Goverde, 2020a, 2020b). However, if the occurrence of a perturbation is known a priori, it is possible to begin rescheduling trains and passengers in advance (i.e., before the perturbation occurs), such that the performance of train operations and passenger services can be improved (Zhan et al., 2015). Data-driven approaches have shown promise for perturbation occurrence prediction in railway systems, as historical data are becoming increasingly available (Fink et al., 2013, 2015). From a system point of view, metro operators can improve the resilience of a metro system by making accurate predictions of the expected number of perturbations of a specific type at a station and taking appropriate mitigation measures (Yap et al., 2019). At the railway operational level, Schön and König (2018) first considered potential delays in railway delay management and applied a stochastic dynamic programming approach to solve the stochastic railway delay management problem. Their test results demonstrated that lower overall delays were achieved when the potential occurrence of perturbations was taken into account, compared to deterministic delay management approaches. However, stochastic TTR considering potential perturbations has not been well investigated and deserves more attention, given the requirements of railway practice.

In summary, various approaches have been employed to address TTR with uncertainty in perturbation information, each with its own advantages and disadvantages. The RHA/MPC is suitable for situations where perturbation information updates regularly but remains relatively stable and known over a period of time. However, it necessitates multiple TTR iterations, making it time-consuming and less accurate. Stochastic programming is appropriate for cases where perturbation information follows a known distribution and can be easily modeled by a limited number of scenarios. Likewise, fuzzy programming is suitable when perturbation information can be readily modeled by a fuzzy set. Both stochastic and fuzzy programming offer good accuracy in solving the TTR problem in a single run, but obtaining a suitable distribution set of perturbation information can be challenging. In contrast, robust optimization does not require a known distribution of perturbation information but may demand considerable time to compute an optimal solution when dealing with complex uncertainty sets. Finally, data-driven approaches show promise in estimating perturbation information and solving TTR efficiently. However, they necessitate a substantial amount of historical data on perturbation information. Ultimately, the choice of approach depends on the process, operations, and data collection procedures. As such, it is crucial to select an appropriate method based on the specific problem at hand.

5.2. Uncertain train running time and dwell time

The running of trains is a dynamic process that is affected by various factors, including weather conditions, driver behaviors, and the interlocking system (Davydov et al., 2017). Additionally, train dwell time is impacted by the actual passenger boarding and alighting process (Cornet et al., 2019). As a result, both a train's running time in a segment and its dwell time at a station possess uncertainty (Hong et al., 2021). In this subsection, previous studies on TTR, which have adopted various approaches to take uncertain running time and dwell time into account, are reviewed. These studies are summarized in Table 2.

(1) Scenario-based deterministic approach

In a TTR model, a train's uncertain running time in a segment and dwell time at a station can be modeled using scenarios. For example, if both the minimum average running speed (v_{min}, no less than zero) and maximum average running speed (v_{max}) of a train in a segment are known, then it can be assumed that the real running time is a series of scenarios (i.e., discrete speed levels) between $\frac{l}{v_{max}}$ and $\frac{l}{v_{min}}$, where l is the length of the segment (Xu et al., 2017; Zhan et al., 2022b). When trains are rescheduled in response to a perturbation, the actual running time and dwell time are chosen from the given scenario set to improve the performance for specific objectives such as minimizing train delay and reducing energy consumption. Although various speed levels (Xu et al., 2017; Luan et al., 2018; Zhan et al., 2022b) and various dwell times in an interval (Meloni et al., 2021) have been considered, only one proper speed level has been selected in the final solutions of the aforementioned studies. This implies that the dynamic characteristics of running time and

Table 2
Studies on TTR with uncertain train running times and dwell times.

Uncertainty	Approach	Detailed strategy	References
Running time and dwell time	Scenario-based deterministic approach	Optimize the train schedules by choosing a specific train running or dwell time in a given scenario set	Xu et al. (2017), Luan et al. (2018), Meloni et al. (2021), Zhan et al., (2022b)
	Stochastic programming	Optimize the train schedules under various scenarios with known probabilities or distributions of train running and dwell times	Meng and Zhou (2011), Shakibayifar et al. (2018), Zhang et al. (2021), Hassannayebi et al. (2021)
	Data-driven approach	Optimize the train schedules using train running and dwell times predicted from historical data	Lessan et al. (2018), Huang et al. (2020), Wang et al. (2020), Reynolds and Maher (2022)

dwell time have not been adequately considered. This method of managing uncertainty is denoted as a scenario-based deterministic approach. The advantage of this approach is that the problem can be easily modeled as a mixed-integer linear programming model and solved using a commercial solver when the number of scenarios is small; i.e., the chosen set for the running time or dwell time is not excessively large, such that the number of decision variables is limited.

(2) Stochastic programming

In stochastic programming, the dynamic train running time and dwell time can be regarded as various scenarios, which is similar to the scenario-based deterministic approach. However, when optimizing train schedules in response to a perturbation, all of the scenarios with known probabilities are considered instead of only one scenario being chosen. Meng and Zhou (2011) employed stochastic programming with a recourse model framework to manage uncertainties in both the segment running time and perturbation duration. Zhang et al. (2021) acknowledged that not all of the scenarios exist in practice and, as a result, a scenario-based chance-constrained predictive control approach (i.e., chance-constrained programming) was applied to ensure that the obtained train disposition timetable was feasible within a certain percentage (e.g., the obtained solutions are feasible under 95 % of all the scenarios). In other words, the constraints were allowed to be partially violated (e.g., some constraints are allowed to be violated under some worst-case scenarios). In this manner, the solution exhibited good robustness (i.e., the solution is feasible for most scenarios) but low conservativeness (i.e., the solution is not necessarily feasible for the worst-case scenarios).

Instead of using discrete running times and dwell times (i.e., scenarios), some studies have assumed that running times follow a specific distribution, such as a log-logistic probability density function (Lessan et al., 2018) or a normal distribution (Shakibayifar et al., 2018; Hassannayebi et al., 2021), while the train dwell time at a station tends to be regarded as a function of the passenger boarding and alighting rates (Hassannayebi et al., 2021). Consideration of such uncertainties in a stochastic optimization model usually makes the model difficult to solve in real time. Therefore, a simulation–optimization-based solution framework has been introduced by Shakibayifar et al. (2018) and Hassannayebi et al. (2021) to obtain a robust train disposition timetable with given distributions of uncertain factors. However, parameters involved in the distribution of running time or dwell time are typically predicted and calibrated in a static manner (i.e., based on the daily traffic status), with dynamic traffic status and other factors (i.e., emerging conditions) not being considered (Davydov et al., 2017; Corman and Kecman, 2018), whereas the real distribution is strongly related to the current traffic status and driver behavior, so this needs to be further investigated (Davydov et al., 2017). Furthermore, two trains may not be able to run according to their best running times on a segment within the given distributions because of the state of the interlocking system. That is, there is a limitation that ensures a safety headway between two consecutive trains running on a segment at any time, so the two consecutive trains are correlated. However, to the best of our knowledge, the impacts of this correlation of the running time or dwell time distributions of any consecutive trains have not been well investigated. For example, the trajectory for a single train was optimized in Wang et al., (2020) and Zhan et al., (2022b), but the correlation among multiple train trajectories were not taken into consideration.

(3) Data-driven approach

Determining the proper scenarios or distributions of the train running time and dwell time is a critical task in stochastic TTR. As mentioned above, some studies have either assumed several discrete scenarios for uncertain train running time or dwell time based on a normative approach (Xu et al., 2017; Zhan et al., 2022b), or have modeled the distribution of the uncertain running time or dwell time via physics-based approaches (Reynolds & Maher, 2022). However, such approaches can yield scenarios or distributions that are inconsistent with the actual situation. This problem can be overcome by applying data-driven approaches, in which real-world data are used to calibrate scenarios or distributions (Lessan et al., 2018). In addition, data-driven approaches can be helpful for reducing the number of running-time scenarios, as instead of a large number of assumed scenarios, a limited number of scenarios obtained from real-world data can be effective and efficient for TTR with variable train running speeds (Reynolds & Maher, 2022). For example, it was found in Reynolds & Maher (2022) that only two or three segment running time scenarios identified from real historical data were representative of the variable speed (i.e., running time distribution) in TTR problem.

To improve the quality of running time prediction, Huang et al. (2020) devised a hybrid model comprising a support vector regression (SVR) and a Kalman filter (KF), where the SVR was trained with offline data and the KF used online information to update the prediction of the SVR. In contrast to most previous studies that predict uncertain train running and dwell times using data-driven approaches, which are then combined with TTR algorithms, some data-driven approaches can be applied to directly address TTR with uncertainty. For example, Yin et al. (2015) transformed the metro train running process into a Markov decision process with non-deterministic state transition probabilities in order to manage uncertain train running and dwell times within TTR. Given that the micro train trajectory in a railway segment between two stations is affected by traction force and train resistance, Wang et al. (2020) optimized a real-time train trajectory through approximate dynamic programming to minimize the deviation between the real segment running time and planned running time, as well as the energy consumption. However, as mentioned by the authors, only a single train running on a segment was considered, and multiple-train trajectory optimization in an uncertain environment needs to be further investigated.

In summary, a scenario-based deterministic approach is appropriate for situations where train running and dwell times can be estimated using a limited number of scenarios. While this method is easy to implement, its accuracy may be lacking. On the other hand, a stochastic programming approach typically yields more accurate solutions but necessitates prior knowledge of running time and dwell time scenarios. Lastly, data-driven approaches offer advantages in estimating running and dwell times, as well as efficiently

Table 3
Studies on TTR with uncertain passenger demand and received information.

Uncertainty	Approach	Detailed strategy	References
Passenger demand	Deterministic optimization approach	Optimize the passenger assignment and train timetables in a deterministic model	Cadarso et al. (2013), Binder et al. (2017), Veelenturf et al. (2017), Zhu & Goverde (2020a), Zhan et al. (2021), Luan & Corman (2022)
	Stochastic programming	Optimize the train timetable under various scenarios with known probabilities or a distribution of passenger demands	Yin et al. (2016), Yin et al. (2022), Mo et al., (2023b)
	Robust optimization	Optimize the passenger route choice when passenger demands follow an uncertainty set	Mo et al. (2023a)
Received information	Simulation-based approach	Simulate the passenger choice behaviors under varying received information	Zhu & Goverde (2019); Leng & Corman (2020)
	Mathematical modeling approach	Model the passenger choice behaviors under incomplete received information using a discrete choice model	Corman (2020); Leng & Corman (2022)

solving TTR problems with uncertain running and dwell times. However, these approaches rely on the availability of extensive, high-quality historical data on train running and dwell times.

5.3. Uncertain passenger demand

As mentioned above, studies have increasingly focused on passenger-oriented train rescheduling, where passenger-performance indicators (e.g., passenger delay) instead of train-operation indicators (e.g., train delay) are considered in the objective function of a TTR model (Josyula & Törnquist Krasemann, 2017). Although the consideration of uncertain passenger demand in TTR is related to the passenger-oriented TTR problem, this review is focused on research concerning uncertain passenger demand and passenger choice behavior. TTR with a fixed or pre-given passenger volume in the weighting of the objective function without considering real-time passenger routing (Espinosa-Aranda & García-Ródenas, 2013) is not within the scope of this review. Reviews by Binder et al. (2015) and Josyula & Törnquist Krasemann (2017), which discuss more studies on passenger-oriented TTR, are recommended for interested readers. In this subsection, studies that have used one of four approaches are summarized in Table 3.

(1) Deterministic optimization approach for uncertain passenger demand

Passenger behavior in the event of a perturbation is difficult to predict because it is affected by many factors, such as the traffic status, perturbation situation, alternative route information and passenger characteristics (Kunimatsu & Hirai, 2014a; 2014b). In most studies, it has been assumed that passengers change their routes in response to a perturbation, but passenger demand remains unchanged unless the demand cannot be fulfilled by train, resulting in mode changes of some passengers. (Cadarso et al., 2013; Binder et al., 2017; Veelenturf et al., 2017; Zhu and Goverde, 2020a; Zhan et al., 2021; Luan & Corman, 2022). In the above-cited studies, passengers have been divided into groups and each group has either been assumed to choose the route with the lowest disutility, such as the route with the lowest general cost (i.e., the passenger group is not split), or has been assumed to choose routes from a given path set (i.e., the passenger group is split) to complete their journeys. Although the passenger demands have remained the same as those in the normal situation, the route-changing behavior of the passengers has affected the specific demand for a route, which has affected train rescheduling strategies in the event of a perturbation.

Cadarso et al. (2013) generated passengers' available routes before a new disposition timetable was available, such that passengers might not have kept to their preassigned routes when information on the new timetable was available. Obviously, passenger route assignment and timetable rescheduling affect each other and such interactions can be dealt with by an iterative approach (Veelenturf et al., 2017). Recently, integrated models have been applied to enable improved management of dynamic passenger assignment and TTR (Binder et al., 2017; Zhu & Goverde, 2020a; Zhan et al., 2021; Luan & Corman, 2022). However, solving an integrated model for real-world large cases within a short computational time is challenging. In addition, a seat reservation system has not been used in the above studies except by Zhan et al. (2021); instead, passengers have been allowed to freely choose their routes, creating shortest-path searching or discrete choice models that are suitable for passenger route choice modeling. However, when a seat reservation system is applied, such as on Chinese Railway and European High-speed Railway, passengers cannot freely choose their routes in the event of a perturbation because they have to change their tickets before boarding an unplanned train. Under these conditions, a passenger's route choice behavior strongly relates to his/her own and others' ticket-booking statuses and other passengers' ticket-changing behaviors, owing to the limited capacity of an individual train. Thus, accurately modeling passenger choice behavior for a railway network with a seat reservation system is quite different from doing so in a railway network without a seat reservation system (Zhan et al., 2021); this remains an open topic of research that requires further investigation. As studies have solved passenger assignment and TTR using a deterministic model (Cadarso et al., 2013; Veelenturf et al., 2017; Binder et al., 2017; Zhu & Goverde, 2020a; Zhan et al., 2021; Luan & Corman, 2022), this is considered a deterministic optimization approach.

(2) Stochastic programming approach for uncertain passenger demand

The above-mentioned studies have adopted a deterministic optimization approach to solve passenger assignment and the TTR problem by assuming that passenger demands are known and remain the same as those without a perturbation. It was simply assumed that passengers did not remain in the railway system if they could not finish their journeys within a given travel time budget. However, in practice, passenger demand varies in a disrupted situation; e.g., some passengers may abandon their planned journeys and some may even abandon traveling by train and change to other transport modes. Therefore, real passenger demand is uncertain. In addition, passengers may have multiple alternative routes to choose in a dense railway network in the event of a perturbation, and the route they actually use is not only dependent on the rescheduled timetable but also the characteristics (travel purposes, age groups, income, gender, etc.) of these passengers. The assumption that passengers choose the route with the lowest disutility is strong, and furthermore, the disutility function normally has a random error term (Xie et al., 2020). Therefore, stochastic programming is suitable for coping with the demand uncertainty and route choice uncertainty of passengers.

In the case of a metro system, Yin et al. (2016) assumed that the volume of passengers arriving at a station followed a statistical distribution (e.g., a Poisson distribution) and introduced a stochastic programming model to solve the TTR problem with passenger uncertainty. They accelerated the solution process by applying an approximate dynamic programming-based algorithm to solve the model. Yin et al. (2022) did not assume that the passenger demand followed a distribution; instead, they assumed passenger-demand scenarios with given probabilities based on historical data to model the uncertain passenger demand and formulated a two-stage stochastic programming model for integrated backup rolling stock allocation and TTR. Li et al., (2015, 2016) and Moaveni &

Najafi (2017) assumed that passenger arrival flow followed a specific distribution and then employed a state-space train traffic model to address uncertainty in train regulation. In contrast, Wang et al. (2022) considered the passenger arrival rate as a fuzzy variable rather than a distribution, and utilized a fuzzy state-space model to tackle metro train regulation issues. As mentioned above, obtaining a good distribution or demand scenario set is critical for these stochastic programming approaches. With data on passenger demand becoming increasingly available, statistical analysis or other data-driven approaches can help to generate more practical passenger demand forecasts than those which have been previously generated (Kunimatsu & Hirai, 2014a, 2014b; Li et al., 2020).

Stochastic programming has rarely been adopted to cope with TTR with uncertain passenger demand in mainline railway systems. This may be because (1) passenger demand is more difficult to predict on railway systems than on metro systems, such that a proper distribution or scenario set for passenger demand is not easy to obtain, and (2) the integrated passenger assignment and TTR model for a mainline railway network is more difficult to solve within a short computational time than that for a metro network, because the structure of a mainline railway network is much more complicated and passengers have more alternative itineraries on a mainline railway network, such that the consideration of uncertain passenger demand in a stochastic manner increases the difficulty of the problem for a mainline railway system. Nevertheless, although passenger route choice behavior in the event of a perturbation is difficult to predict, analysis can be performed using historical data, such as smart card data (Van Der Hurk et al., 2014) and travel survey based on GPS tracking and Automatic Vehicle Location (AVL) data (Marra & Corman, 2023). It has been noted that passengers can be recommended routes from a system point of view in the event of a perturbation, but passengers may not always follow such recommendations. Owing to the capacity limits of trains, if a passenger group does not follow a recommended route, the choice behaviors of other passenger groups are affected. Therefore, the uncertainty of passengers following recommended routes should be modeled. Mo et al. (2023b) assumed that passengers accepted recommended routes with a probability distribution and introduced two concepts ($\epsilon -$feasibility and $\Gamma -$concentration) to control the mean and variance of path flows in a stochastic optimization model. In fact, which route is actually selected by a passenger is greatly affected by the information the passenger receives regarding traffic status, as analyzed in subsection 5.4.

(3) Robust optimization approach for uncertain passenger demand

Uncertain passenger demand in a railway system under a perturbation can be modeled using an uncertainty set, such that robust optimization appears suitable for performing TTR with uncertain passenger demand. However, robust optimization has rarely been adopted to solve this problem: an exception is that Mo et al. (2023a) applied robust optimization to recommend paths to passengers in the event of a perturbation and with consideration of passenger demand uncertainty. They used an ellipsoidal uncertainty set and three polyhedral uncertainty sets to model uncertain passenger demand in the event of a perturbation, and their results showed that the most robust model reduced the average passenger travel time by 2.91 %. Although robust optimization has seldomly been applied in TTR with uncertain passenger demand, it has been used to solve a similar problem, namely train scheduling (train timetabling) with uncertain passenger demand (see, e.g., Cacchiani et al., 2020; Lu et al., 2022). The two main differences between train timetable

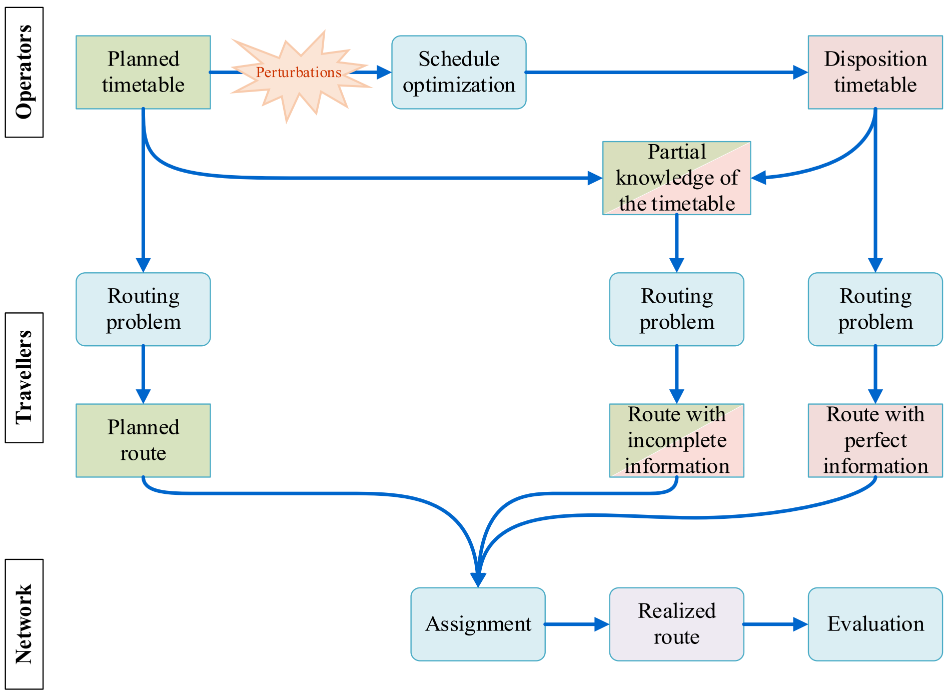

Fig. 5. Flowchart of passenger route choice on a network with various traffic information (Leng & Corman, 2020).

scheduling and rescheduling under uncertain demand are that (1) more historical passenger demand data are available for train timetable scheduling than for timetable rescheduling, because similar perturbations rarely occur in train operations (especially for a serious incident that may occur only once within tens of years), and (2) it is acceptable to solve the train timetable scheduling problem within a computational time longer than that for the TTR problem, because the latter problem needs to be solved in real time. With increasing amounts of passenger demand data becoming available and the increasing computational capability of computers, it is expected that robust optimization will be widely used for solving TTR with uncertain demand in future studies.

In summary, the deterministic optimization approach is commonly employed in TTR with uncertain passenger demand, as it models passenger choice behavior using a discrete choice model. This approach is suitable for situations where total passenger demand remains relatively stable and passenger choice behavior is fairly simple. Stochastic programming and robust optimization, on the other hand, necessitate knowledge of demand scenario sets and demand uncertainty sets, respectively. Although these methods may yield higher quality solutions compared to the deterministic optimization approach, they face challenges in solving TTR with uncertain passenger demand in real-time.

5.4. Uncertainty in the information received and considered by passengers

Timely and correct information is critical for TTR, because it helps railway dispatchers to efficiently reschedule disrupted trains and meanwhile assists passengers to properly replan their journeys and thus reduces the impact of a perturbation. However, in practice, exact information is difficult to obtain and send to railway staff and passengers in a timely manner, so a perturbation has a large impact on both railway operations and passenger services. A flowchart showing passenger route choice on a railway network with varying traffic information is presented in Fig. 5 (Leng & Corman, 2022). After a perturbation occurs, railway operators optimize the planned timetable to obtain a disposition timetable, and passengers then replan their routes according to the information they receive about the disposition timetable. If only partial information on the disposition timetable is available, they replan their routes according to both the information on the original planned timetable and the partial information on the disposition timetable. However, if complete information on the disposition timetable is available, passengers replan their routes only according to the disposition timetable. Thus, passengers' replanned routes tend to be strongly related to available information, and the performance of a network varies when evaluated in terms of realized passenger routes.

Most studies have assumed that perfect information is available for TTR to reduce the complexity of the problem (Corman, 2020; Leng & Corman, 2020, 2022). However, recently, some studies have considered untimely and incomplete information in passenger routing under a perturbation, which is an important component of passenger-oriented TTR. The findings of these studies are presented in Table 3 "Received Information" and are discussed in greater detail below.

(1) Simulation-based approach for handling uncertainty in passenger-received information

Zhu & Goverde (2019) modeled dynamic passenger assignment on a railway network in the event of a large perturbation, in which train cancelling and short-turning were required. Instead of assuming that passengers had perfect information on the disposition timetable and congestion of scheduled trains, they considered the effect of imperfect information on passengers' choices. Specifically, they simulated passenger route choice behavior when passengers received information at different locations (i.e., only at railway stations or both at stations and on trains) in a discrete-event simulation. As passengers could only receive the part of the information that was available at a specific location, they made their route choice decisions according to this myopic information. The authors noted that their passenger assignment model had the potential to be embedded in the TTR model to produce a better passenger-oriented train disposition timetable than the existing TTR model. Leng & Corman (2020) further investigated the role of information in passenger choice behaviors on a multimodal transport network using a novel four-dimensional (who–when–where–what) framework. They compared passenger behaviors and passenger service qualities in the event of a perturbation with no information, timely information (i.e., information being available at the occurrence of a perturbation) and advanced information (i.e., information being available before the occurrence of a perturbation) on an agent-based simulation platform (MATSim). Their test results showed that knowing information earlier was better than knowing information later, but the differences between the solutions obtained with advanced information and those obtained with timely information were small. Thus, obtaining complete information at the occurrence of a perturbation is critical to passenger service quality in the event of a perturbation.

(1) Mathematical modeling approach for managing uncertainty in passenger-received information

Leng & Corman (2022) relaxed the assumption that complete, correct and timely information was available, as has been assumed in most studies on passenger-oriented TTR in the event of a perturbation. Instead, they considered that only part of the information within a limited time period was available and that passengers had different beliefs about future information. They devised a belief–desire–intention model of passenger route choice behavior to minimize travel time when incomplete information was available. They tested their model on part of the Dutch Railways network and compared the passengers' expected delay with the real delay. Although the impacts of incomplete, untimely and incorrect information on passenger route choices were analyzed, the analysis result was not applied to the TTR problem. Corman (2020) used a game theoretical approach to study the effect of the interaction between TTR and passenger routing with consideration of varying partial information on the current status of traffic flows. As the current traffic status under a perturbation was uncertain to passengers, the selected routes tended to be different from the routes advised by railway infrastructure managers. The test results showed that increasing the amount of information available to passengers improved the solution. However, the assumption was made that full information about the future railway states was available, but as time passes, the information might be updated, causing the railway operator and passengers to potentially change their strategies in reality.

5.5. Summary

This study conducted a comprehensive review of existing literature related to handling TTR with uncertainty. Various types of uncertainties were identified, stemming from demand, supply, and disruption factors. These uncertainties impact the decisions made by both railway operators and passengers, highlighting the importance of effectively addressing them in TTR. The suitability of different approaches for managing these uncertainties was analyzed based on previous studies, along with an evaluation of the advantages and disadvantages of each approach for specific research problems.

6. Discussion and future research directions

6.1. Discussion

In this paper, studies on TTR under uncertainty have been comprehensively reviewed. The main uncertain aspects of TTR based on railway operation practice were first identified, and then studies that have applied various approaches to handle these uncertain aspects were reviewed. Uncertainty has been increasingly considered in TTR in the past decade. However, although most studies have considered uncertain perturbation duration and uncertain passenger demand in TTR, uncertain train running time and dwell time and uncertainty in which information received and considered by passengers and railway staff in TTR have drawn little attention. In addition, dynamic changes of perturbation status, has not been investigated neither.

Accurate prediction of the uncertain aspects existing in TTR is crucial for the optimization of TTR problems. In principle, more precise predictions can be achieved as time progresses or when more historical data about past perturbations becomes available. Some types of uncertainty are relatively more challenging to predict because these uncertain events rarely occur and show little/no signs even at the moment approaching their actual occurrences. This concerns the predication about whether and when a large disruption occurs. In contrast, most uncertain events are unknown far in advance but become partially known as the prediction time gets closer to their actual occurrences. After a perturbation occurs, the prediction is mostly about the duration of a perturbation, the running time and dwell time of a train, and the passenger demand and information received by passengers. In the latter case, the timing of the prediction is essential. If the prediction is made too far in advance, it may not be accurate enough to guide the subsequent optimization of TTR, although more time would be available for the preparation/reaction towards the perturbation. On the other hand, if the prediction is made closer to the event, it tends to be more accurate, but less time is available for the preparation/reaction. Therefore, a trade-off exists between the prediction time (accuracy) of uncertain events and the subsequent implementation of TTR.

To better manage the uncertainty of train running and dwell times, the TTR problem needs to be considered and modeled at a microscopic level (i.e., modeling the detailed train speed profile), which will substantially increase the complexity of the problem. This may be overcome by employing a simulation–optimization-based approach, in which dynamic running and dwell times are quickly simulated at a microscopic level and then embedded into a macroscopic optimization model for TTR. It is not easy to model the effect of uncertain received information on TTR and passenger assignment, and only a few studies have conducted simulations to analyze the impact of uncertain received information on passenger route choice. This research area is in its embryonic stage, and incorporating the effects of uncertainty in the information received and considered by passengers into TTR remains an open question. Finally, the various uncertain aspects mentioned above are not isolated, and several uncertainties may exist simultaneously in a real-time TTR problem. Therefore, the study of how to handle various (correlated) uncertainties in TTR to obtain a more robust disposition timetable (from the perspectives of passengers) is required.

The advantages and disadvantages of existing approaches to solve the TTR problem with different uncertain aspects are discussed, and the difficulties hindering the application of these approaches are analyzed as follows.

- Heuristic approaches, such as RHA, have been used to deal with various uncertainties in TTR; in these approaches, TTR performed step by step according to newly updated information in a closed-loop fashion. Although these heuristic approaches are easy to implement and likely to be solved within a short computational time, their solution quality and robustness are not guaranteed because the model for each stage is deterministic or its stochasticity is considered in a very limited manner.
- Stochastic programming and robust optimization have been applied to managing the uncertainty in TTR. Although solutions of greater robustness can be obtained by using these two approaches than by using other approaches (e.g., RHA), the computational time for a stochastic model or a robust model tends to be long, which hinders their application to the real-time TTR problem. Consequently, constructing a proper scenario or uncertainty set is important for reducing the computational complexity of stochastic programming or robust optimization. The emerging data-driven approaches have the potential to facilitate the construction of an appropriate scenario or uncertainty set based on multiple-source historical data.
- Data-driven approaches are helpful in predicting uncertain information involved in TTR, which is useful for guiding the subsequent decision-making process for TTR. The accuracy of the prediction is significantly affected by the time when the prediction is made, i.e., the variability reduces when the event to be predicted gets closer in time. Because the operator needs time to make and implement a rescheduling decision, a trade-off between the prediction accuracy and implementation feasibility exists, and the proper time to make the prediction should be well determined.

While we have previously discussed the significance and potential benefits of accurately predicting various uncertainties in TTR for railway operators and passengers, achieving this accuracy in practice continues to be a challenge. In the following section, we present our understanding of the primary factors contributing to this difficulty, based on our literature review. We have categorized these factors under the keywords of quality, timeliness, optimization, and implementability.

First, achieving a high quality of prediction is challenging due to the dynamic nature of railway systems and the occurrence of unforeseen events, such as disturbances. Prediction accuracy can be improved to a certain degree if a sufficiently large dataset is collected, under the assumption that all relevant phenomena are represented in the historical data and the system will continue to operate under the same dynamics in the future. However, there are practical limitations to this assumption, which are related to significant system changes (e.g., data measured before and during COVID lockdowns), adjustments to supply (such as implementing a new timetable with more or different trains), and small yet unavoidable changes (for instance, increased demand leading to slightly longer average dwell times over time). Generally, employing sophisticated approaches can result in a higher quality of prediction.

Second, while quality can be exceptionally high for events occurring close in time, the goal is to provide timely predictions for events sufficiently ahead of time. As discussed in Büchel & Corman (2022), an appropriate prediction horizon characterizes the predictability of processes and allows for the estimation of prediction accuracy and its uncertainty. Specifically, total uncertainty can be divided into aleatoric and epistemic components. The former can be reduced by improving data collection methods for currently unobserved variables, while the latter can be reduced by utilizing more advanced prediction methods. However, the improvement in predicting epistemic uncertainty is limited when the prediction horizon is long in train delay prediction (Spanninger et al., 2023). To better assist railway operators and passengers during disturbances, both the prediction accuracy and the associated confidence level can be provided, enabling better decision-making based on both accuracy and confidence, even if the accuracy is not perfect (Spanninger et al., 2023).

Third, even with a highly accurate description of uncertainty, incorporating it into optimization is not straightforward, as appropriate models and objective functions may need to be selected, as discussed in the reviewed approaches.

Lastly, implementing a comprehensive toolchain that links data, prediction, optimization, and decision-making can be complex and may not be readily accepted without a thorough assessment of risks and benefits. Human decision-makers might believe they have a better understanding of the system, as some key data may not be included in the entire toolchain (examples include weather, network status, and unexpected passenger flows). Consequently, they might have valid reasons to deviate from the suggested optimized

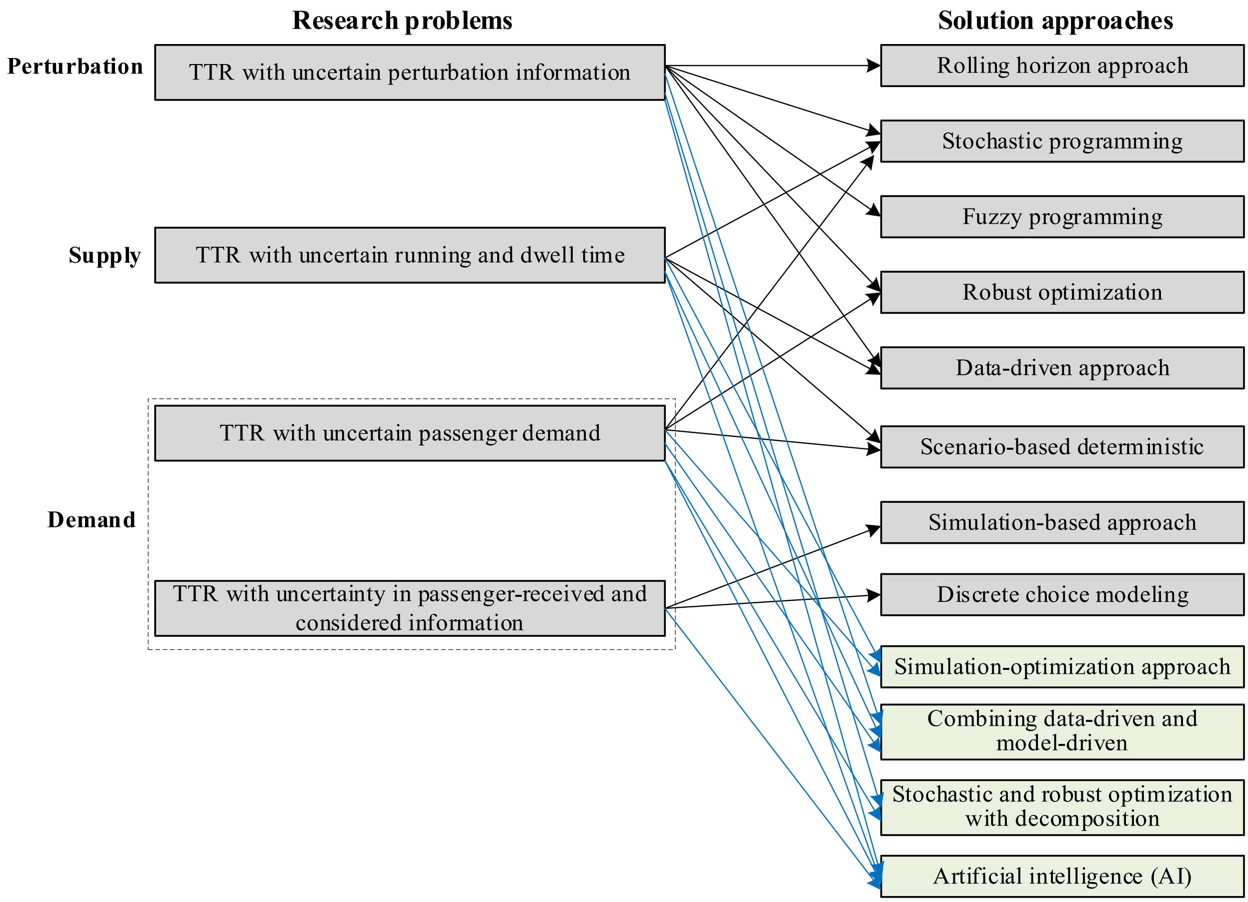

Fig. 6. Existing problems and potential solution approaches.

solutions.

6.2. Future research directions

Several research directions have been proposed to potentially guide future studies on the basis of the above discussions and fulfil the research gaps identified in this comprehensive review. Urgent research questions that require investigation from the perspective of railway practice (section 6.2.1), as well as potential appropriate approaches for efficiently addressing the uncertainty aspects of TTR (section 6.2.2), are included in these directions. Recall that in Fig. 3, we show the existing research questions and solution approaches. We extend this figure to Fig. 6, where we additionally suggest new solution approaches (the light green rectangles) to the existing research questions. Fig. 7 illustrates the proposed future research questions along with the potentially applicable solution approaches. In Fig. 7, we do not link each future research problem to every potential solution approach and vice versa. Determining all the possible suitable solution approaches for each problem is challenging at this stage, as the appropriateness of a method often necessitates actual exploration and demonstration. Fig. 7 aims to indicate the possibility rather than suitability of these solution approaches. Furthermore, some problems can be addressed by multiple approaches, and some solution approaches may encompass multiple problems. As a result, illustrative arrows in both directions are employed in Fig. 7 to demonstrate these relationships. Lastly, AI-based approaches have a broad scope in today's world. Determining the most suitable AI-based solution approach (e.g., deep learning or reinforcement learning) for a specific question requires further investigation.

6.2.1. Research questions

In this subsection, future research questions from perturbation side, supply side, demand side, and integrated side of perturbation, supply, and demand, as mentioned in Section 4, are identified.

(1) Perturbation side

- Managing uncertain perturbation status

Through close collaboration and discussions with Chinese railway dispatchers, it has been determined that the dynamic changes in perturbation statuses significantly hinder the implementation of an automatic train dispatching system. The uncertainty of a perturbation not only involves its unpredictable duration but also its subsequent status, such as a speed limit or a segment closure. To the best of the authors' knowledge, no studies have considered this uncertain status of perturbations in TTR; however, it warrants special attention for practical real-world applications.

(2) Supply side

- Improvement of the robustness of a disposition timetable in the event of a perturbation

Robustness is one of the indicators for train timetabling (Corman et al., 2014; Solinen et al., 2017), but it has rarely been considered in TTR. Supplements, which correspond to train running time in a segment and dwell time at a station, contribute to the robustness of a train timetable. To date, the uncertainties of train running time and dwell time in TTR have not been well investigated. For example, only some scenarios are assumed for the running time and dwell time, and the correlation of them between consecutive trains is not considered. This results in low applicability and robustness of a disposition timetable obtained by the current TTR methodologies

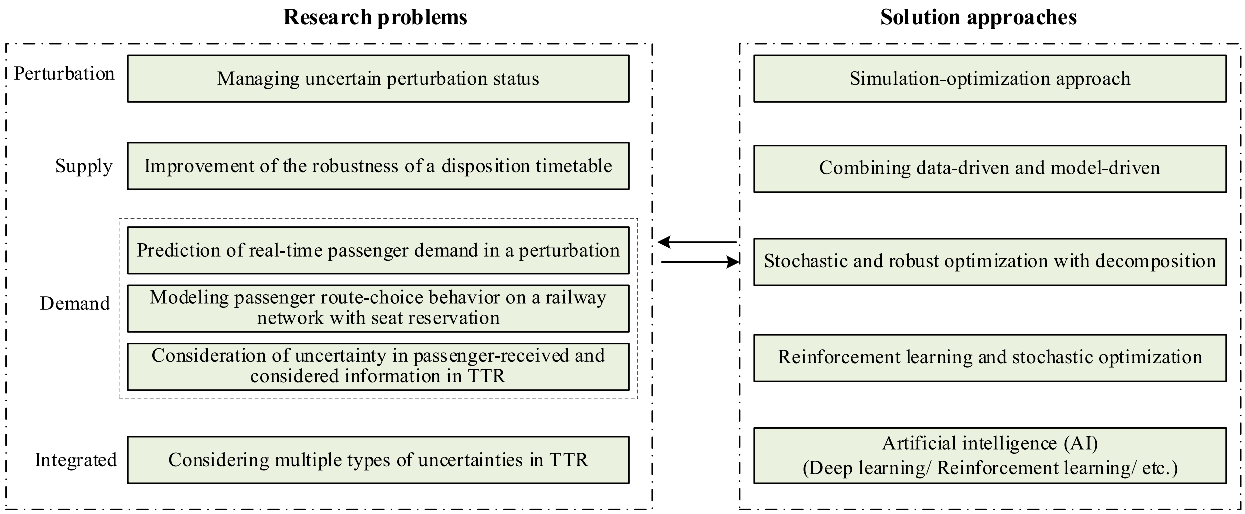

Fig. 7. Future research problems and potential solution approaches.

(Reynolds & Maher, 2022). Therefore, it is essential to investigate how to improve the prediction and modeling of uncertainties in train running time and dwell time, and integrate them into TTR models.

(3) Demand side

- Prediction of real-time passenger demand in the event of a perturbation

As mentioned above, most studies have assumed that passenger demand does not change in response to a perturbation, that is, passengers remain in a railway system unless they cannot reach their destinations within a given general cost. However, in the event of a large perturbation, some passengers tend to abandon their planned path choices or even change to other transport modes. Therefore, the number of passengers remaining in a railway system decreases at a rate that tends to be different for each origin–destination pair because of the heterogeneity of itinerary and passenger characteristics. Predicting the real-time passenger volume (or volume distribution) for each origin–destination pair in the event of a perturbation is important for real-time passenger-oriented TTR.

- Consideration of uncertainty in the information received and considered by passengers in TTR

As noted by Leng & Corman (2020, 2022), in practice, the information (e.g., the current train timetable and information on network congestion) received by a passenger is usually incomplete, out of date and imprecise, which affects passenger route choice behaviors and thus TTR in the event of a perturbation. However, few studies have simulated the impact of uncertain received information on passenger route choice, and the impact on TTR remains largely unexplored. Therefore, to obtain a disposition timetable that well matches real passenger demand, the impacts of uncertain received information on passenger choice behavior and TTR should be jointly considered in future research.

- Modeling passenger route-choice behavior on a railway network with a seat reservation system

Passengers cannot freely change their routes on a railway network with a seat reservation system (e.g., Chinese railways and European high-speed railways) because they have to change their tickets in advance. Therefore, passenger route choice behavior on a railway network with a seat reservation system is different from that on a railway network without such a system. Due to the heterogeneity of passengers, it is not easy to predict or model who are likely to change their routes. Furthermore, a passenger's decision to change the route can have a ripple effect on the choices of other passengers due to seat reservations and limited train capacity. Therefore, the traditional shortest-path model or discrete choice model cannot be directly used to model passenger route choice on a railway network with a seat reservation system. For future studies, more advanced modeling approaches are needed.

(4) Integrated disruption, supply and demand side

- Considering multiple types of uncertainties in TTR to obtain robust solution

In most previous studies, only one or two types of uncertainties (e.g., only the uncertain duration of a perturbation or both the uncertain duration of a perturbation and the uncertain train running time) mentioned above are considered. However, in real-world TTR problems, it is possible that more types of uncertainties are involved, and some of them are correlated, such as the uncertainty in information received/considered by passengers and the uncertainty in passenger demand. Investigating how to solve TTR problems considering all the involved (correlated) uncertainties to obtain a more robust solution is important and required. However, it is more complicated to jointly determine the probability of various types of stochasticity, and furthermore, estimating the probabilities of some rare events is challenging. Therefore, future studies are required to overcome these difficulties.

6.2.2. Potential solution approaches

- Simulation–optimization approach for solving TTR under uncertainty

As TTR is a real-time problem, an integrated TTR model that considers existing uncertainties is likely to be difficult to solve, especially when taking dynamic passenger routing or microscopic train running and dwelling into account. A simulation–optimization-based approach seems promising for reducing the computational complexity in situations where dynamic passenger routing or microscopic train running and dwelling processing is performed by simulation, and macroscopic TTR is performed by optimization. Several prior studies have utilized the simulation–optimization approach for addressing TTR with uncertainties, including the application of the Monte Carlo method. Nevertheless, there is still room for enhancement in both the simulation methods and integration techniques within this approach. To further reduce computational time, a simulation process can sometimes be done offline in advance, and the solutions would then be embedded into the optimization process.

- Combining data-driven and model-driven approaches for solving TTR under uncertainty

Data-driven approaches have been widely used for prediction and forecasting in the past several years, and they have the potential utility to generate predictions for uncertainties involved in TTR based on historical data, such as the duration of a perturbation, train running and dwell times, and passenger demand. Through such prediction of complex uncertain components, reasonable scenario and uncertainty sets can be obtained and then used in stochastic and robust optimization models for solving TTR under uncertainty. This approach can also be regarded as an integration of prediction and optimization approaches.

- Stochastic programming and robust optimization with problem decomposition for solving TTR under uncertainty

Stochastic programming and robust optimization are two approaches that are widely applied to problems involving uncertainty. However, their relatively long computational times need to be overcome when applied to TTR under uncertainty. Increasing computer power will facilitate their application in the near future, and decomposition approaches have the potential to reduce the computational time of a TTR model with uncertainty. Thus, stochastic programming and robust optimization with appropriate decomposition approaches are promising options for solving TTR under uncertainty.

- Reinforcement learning and stochastic optimization for solving TTR under uncertainty

Reinforcement learning and stochastic optimization, as proposed by Warren B. Powell, provide a unified framework for making sequential decisions under uncertainty (Powell, 2022). This approach enables decision-making based on the current state and newly acquired information. In practice, TTR is carried out in stages, with progressively more information and/or greater accuracy, making it suitable for modeling as a sequential decision-making process. Various uncertainties can be represented by newly arrived information, allowing for the consideration of multiple uncertainties within the reinforcement learning and stochastic optimization approach.

- Artificial Intelligence (AI) for solving TTR under uncertainty

Unlike mathematical model-based approaches, which usually make several assumptions to simplify the TTR problem, such as fixed train running time and dwell time and identical headway between any two consecutive trains, AI-based approaches can fully utilize real-time structured and unstructured information from the data without those unrealistic assumptions (Wen et al., 2019). Therefore, the solution can better consider the inherent uncertainties in TTR. In addition, AI-based approaches, such as reinforcement learning, are either model-free or model-based methods where the agent learns through actions and environment feedback. These approaches hold promise for increasing the scalability and richness of models used in AI-based methods to handle non-linear and complex effects of real-life TTR problems, as long as the data can adequately describe them. This would enable solving TTR problems involving uncertainty more closely to real-world situations.

7. Conclusions

This review has focused on TTR under uncertainty, which is an emerging research area that has not yet drawn much attention. Most studies on TTR have not considered inherent uncertainties, resulting in solutions that are rarely implemented in practice at railway dispatching centers. At least two gaps exist between the previous research and the practical requirement: one is that the obtained disposition timetable tends to be infeasible without considering uncertain train running time and dwell time (Reynolds & Maher, 2022), and the other is that the obtained disposition timetable is not suitable for real-world perturbation updating/changing. Uncertain perturbation information, uncertain train running and dwell times, uncertain passenger demand and uncertainty in which information received and considered by passengers are the main types of uncertainties involved in TTR, and the impacts of these different types of uncertainties on both train operations and passenger services were analyzed in this paper.

Studies on TTR under uncertainty were comprehensively reviewed in terms of the above four types of uncertainties. Most studies on TTR under uncertainty have focused on uncertain perturbation duration and uncertain passenger demand, whereas there has been a lack of investigation on the other types of uncertainties. In terms of methodology, RHA (MPC, the same concept in control theory), stochastic programming and robust optimization are the main approaches that have been adopted to manage TTR under uncertainty. However, the current approaches have drawbacks that hinder the field application of their solutions. To guide future research on TTR under uncertainty, several directions were presented from both the problem perspective and methodology perspective.

In summary, real-time TTR plays a critical role in railway perturbation management, and considering the uncertainties involved in this problem is a practical requirement. Although TTR with consideration of uncertainty has been an emerging research topic in the past decade, it has not been well investigated and is still far from meeting practical requirements. New practical problems need to be considered, and new methodologies such as combined approaches and artificial intelligent approaches have the potential to solve TTR under uncertainty in a timely and high-quality manner. Finally, accurately predicting all the uncertainties involved in TTR might be challenging and impractical. It is reasonable to assert that considering recorded behavior is preferable to disregarding it, and having data to describe the most prominent dynamics of recorded behavior is better than relying on rules of thumb. Consequently, collecting and utilizing more data in a suitably precise prediction method can enhance the understanding of current operations and the predictability of future planned events. These factors can better guide both railway operators and passengers in making informed decisions that cater to their specific goals.

CRediT authorship contribution statement

Shuguang Zhan: Conceptualization, Methodology, Visualization, Writing – original draft. **Jiemin Xie:** Conceptualization, Writing – review & editing. **S.C. Wong:** Conceptualization, Writing – review & editing. **Yongqiu Zhu:** Conceptualization, Writing – review &

editing. **Francesco Corman:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (NSFC) (72171198, 72171182), Natural Science Foundation of Sichuan Province (2022NSFSC1890) and the Fundamental Research Funds for the Central Universities, China (JZ2023YQTD0073). The second author was supported by the Guangdong Basic and Applied Basic Research Foundation (2022A1515110235, 2023A1515012542). The third author was supported by the Francis S Y Bong Endowed Professorship in Engineering, and the Guangdong - Hong Kong - Macau Joint Laboratory Program of the 2020 Guangdong New Innovative Strategic Research Fund, Guangdong Science and Technology Department (2020B1212030009). The fourth author acknowledges the support of ETH Zurich Postdoctoral Fellowship.

References

Adelé, S., Tréfond-Alexandre, S., Dionisio, C., Hoyau, P.A., 2019. Exploring the behavior of suburban train users in the event of disruptions. Transport. Res. F: Traffic Psychol. Behav. 65, 344–362.

Binder, S., Maknoon, Y., Bierlaire, M., 2015. Passenger-oriented railway disposition timetables in case of severe disruptions. In: 15th Swiss Transportation Research Conference (No. CONF), Monte Verità / Ascona.

Binder, S., Maknoon, Y., Bierlaire, M., 2017. The multi-objective railway timetable rescheduling problem. Transport. Res. Part C: Emerg. Technol. 78, 78–94.

Binder, S., Maknoon, M.Y., Azadeh, S.S., Bierlaire, M., 2021. Passenger-centric timetable rescheduling: a user equilibrium approach. Transport. Res. Part C: Emerg. Technol. 132, 103368.

Birge, J.R., Louveaux, F., 1997. Introduction to Stochastic Programming. Springer-Verlag, New York.

Borecka, J.T., Bešinović, N., 2021. Scheduling multimodal alternative services for managing infrastructure maintenance possessions in railway networks. Transport. Res. Part B: Methodol. 154, 147–174.

Bortolomiol, S., Lurkin, V., Bierlaire, M., Bongiovanni, C., 2021. Benders decomposition for choice-based optimization problems with discrete upper-level variables. In: 21st Swiss Transport Research Conference, Monte Verità / Ascona.

Büchel, B., Corman, F., 2022. What do we know when? modeling predictability of transit operations. IEEE Trans. Intell. Transp. Syst. 23 (9), 15684–15695.

Cacchiani, V., Huisman, D., Kidd, M., Kroon, L., Toth, P., Veelenturf, L., Wagenaar, J., 2014. An overview of recovery models and algorithms for real-time railway rescheduling. Transport. Res. Part B: Methodol. 63, 15–37.

Cacchiani, V., Qi, J., Yang, L., 2020. Robust optimization models for integrated train stop planning and timetabling with passenger demand uncertainty. Transport. Res. Part B: Methodol. 136, 1–29.

Cadarso, L., Marín, Á., Maróti, G., 2013. Recovery of disruptions in rapid transit networks. Transport. Res. Part E: Logist. Transport. Rev. 53, 15–33.

Cavone, G., Dotoli, M., Epicoco, N., Seatzu, C., 2017. A decision making procedure for robust train rescheduling based on mixed integer linear programming and Data Envelopment Analysis. App. Math. Model. 52, 255–273.

Corman, F., 2020. Interactions and equilibrium between rescheduling train traffic and routing passengers in microscopic delay management: a game theoretical study. Transp. Sci. 54 (3), 785–822.

Corman, F., Kecman, P., 2018. Stochastic prediction of train delays in real-time using Bayesian networks. Transport. Res. Part C: Emerg. Technol. 95, 599–615.

Corman, F., Meng, L., 2014. A review of online dynamic models and algorithms for railway traffic management. IEEE Trans. Intell. Transp. Syst. 16 (3), 1274–1284.

Corman, F., D'Ariano, A., Hansen, I.A., 2014. Evaluating disturbance robustness of railway schedules. J. Intell. Transp. Syst. 18 (1), 106–120.

Corman, F., Quaglietta, E., Goverde, R.M., 2018. Automated real-time railway traffic control: an experimental analysis of reliability, resilience and robustness. Transp. Plan. Technol. 41 (4), 421–447.

Cornet, S., Buisson, C., Ramond, F., Bouvarel, P., Rodriguez, J., 2019. Methods for quantitative assessment of passenger flow influence on train dwell time in dense traffic areas. Transport. Res. Part C: Emerg. Technol. 106, 345–359.

Currie, G., Muir, C., 2017. Understanding passenger perceptions and behaviors during unplanned rail disruptions. Transport. Res. Procedia 25, 4392–4402.

Davydov, B., Chebotarev, V., Kablukova, K., 2017. Stochastic model for the real-time train rescheduling. Int. J Transport Development and Integration 1 (3), 307–317.

Espinosa-Aranda, J.L., García-Ródenas, R., 2013. A demand-based weighted train delay approach for rescheduling railway networks in real time. J. Rail Transp. Plann. Manage. 3 (1–2), 1–13.

Fang, W., Yang, S., Yao, X., 2015. A survey on problem models and solution approaches to rescheduling in railway networks. IEEE Trans. Intell. Transp. Syst. 16 (6), 2997–3016.

Fink, O., Zio, E., Weidmann, U., 2013. Anticipating railway operation disruption events based on the analysis of discrete-event diagnostic data. Chem. Eng. Trans. 33, 715–720.

Fink, O., Zio, E., Weidmann, U., 2015. Fuzzy classification with restricted Boltzman machines and echo-state networks for predicting potential railway door system failures. IEEE Trans. Reliab. 64 (3), 861–868.

García, J., Peña, A., 2018. Robust optimization: concepts and applications. Nature-inspired methods for stochastic, robust and dynamic optimization, InTech. <https://doi.org/10.5772/intechopen.75381>.

Ghaemi, N., Zilko, A.A., Yan, F., Cats, O., Kurowicka, D., Goverde, R.M., 2018. Impact of railway disruption predictions and rescheduling on passenger delays. J. Rail Transp. Plann. Manage. 8 (2), 103–122.

Goverde, R.M., Hansen, I.A., 2013. Performance indicators for railway timetables. In: 2013 IEEE International Conference on Intelligent Rail Transportation Proceedings. IEEE, pp. 301–306.

Govindan, K., Fattahi, M., Keyvanshokooh, E., 2017. Supply chain network design under uncertainty: a comprehensive review and future research directions. Eur. J. Oper. Res. 263 (1), 108–141.

Grandhi, B.S., Chaniotakis, E., Thomann, S., Laube, F., Antoniou, C., 2021. An estimation framework to quantify railway disruption parameters. IET Intel. Transport Syst. 15 (10), 1256–1268.

Hassannayebi, E., Sajedinejad, A., Kardannia, A., Shakibayifar, M., Jafari, H., Mansouri, E., 2021. Simulation-optimization framework for train rescheduling in rapid rail transit. Transport. B: Transport Dyn. 9 (1), 343–375.
Hong, X., Meng, L., Corman, F., D'Ariano, A., Veelenturf, L.P., Long, S., 2021a. Robust capacitated train rescheduling with passenger reassignment under stochastic disruptions. Transp. Res. Rec. 2675 (12), 214–232.
Hong, X., Meng, L., D'Ariano, A., Veelenturf, L.P., Long, S., Corman, F., 2021b. Integrated optimization of capacitated train rescheduling and passenger reassignment under disruptions. Transport. Res. Part C: Emerg. Technol. 125, 103025.
Huang, P., Wen, C., Fu, L., Peng, Q., Li, Z., 2020. A hybrid model to improve the train running time prediction ability during high-speed railway disruptions. Saf. Sci. 122, 104510.
Josyula, S.P., Törnquist Krasemann, J., 2017. Passenger-oriented railway traffic re-scheduling: A review of alternative strategies utilizing passenger flow data. In 7th International Conference on Railway Operations Modelling and Analysis, Lille.
Jusup, M., Trivella, A., Corman, F., 2021. A review of real-time railway and metro rescheduling models using learning algorithms. In: 30th International Joint Conference on Artificial Intelligence (IJCAI 2021), Montreal.
Kunimatsu, T., Hirai, C., 2014a. The prediction of passenger flow under transport disturbance using accumulated passenger data. WIT Trans. Built Environ. 135, 623–634.
Kunimatsu, T., Hirai, C., 2014b. Methods for analyzing passenger flows during train traffic disruption using accumulated passenger data. Quart. Rep. RTRI 55 (2), 86–90.
Lamorgese, L., Mannino, C., Pacciarelli, D., Krasemann, J.T., 2018. Train dispatching. Handbook of Optimization in the Railway Industry 265–283.
Leng, N., Corman, F., 2020. The role of information availability to passengers in public transport disruptions: an agent-based simulation approach. Transport. Res. Part A: Policy Pract. 133, 214–236.
Leng, N., Corman, F., 2022. Communicating delays and adjusted disposition timetables: modelling and evaluating the impact of incomplete information to passengers. Expert Syst. Appl. 191, 116265.
Lessan, J., Fu, L., Wen, C., Huang, P., Jiang, C., 2018. Stochastic model of train running time and arrival delay: a case study of Wuhan-Guangzhou high-speed rail. Transp. Res. Rec. 2672 (10), 215–223.
Li, S., De Schutter, B., Yang, L., Gao, Z., 2015. Robust model predictive control for train regulation in underground railway transportation. IEEE Trans. Control Syst. Technol. 24 (3), 1075–1083.
Li, X., Shou, B., Ralescu, D., 2014. Train rescheduling with stochastic recovery time: a new track-backup approach. IEEE Trans. Syst. Man Cybernet.: Syst. 44 (9), 1216–1233.
Li, S., Yang, L., Gao, Z., Li, K., 2016. Robust train regulation for metro lines with stochastic passenger arrival flow. Inf. Sci. 373, 287–307.
Li, B., Yao, E., Yamamoto, T., Tang, Y., Liu, S., 2020. Exploring behavioral heterogeneities of metro passenger's travel plan choice under unplanned service disruption with uncertainty. Transport. Res. Part A: Policy Pract. 141, 294–306.
Liao, J., Zhang, F., Zhang, S., Gong, C., 2020. A real-time train timetable rescheduling method based on deep learning for metro systems energy optimization under random disturbances. J. Adv. Transp. 2020, 1–14.
Liu, X., Zhou, M., Ma, J., Wang, B., Zhan, S., Dong, H., 2022. A two-stage stochastic programming approach for timetable rescheduling with reassignment of rolling stock under uncertain disruptions. In: 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC), IEEE, Beijing, pp. 4349–4354.
Liu, X., Zhou, M., Dong, H., Wu, X., Li, Y., Wang, F.Y., 2023. ADMM-based joint rescheduling method for high-speed railway timetabling and platforming in case of uncertain perturbation. Transport. Res. Part C: Emerg. Technol. 152, 104150.
Lu, Y., Yang, L., Yang, K., Gao, Z., Zhou, H., Meng, F., Qi, J., 2022. A distributionally robust optimization method for passenger flow control strategy and train scheduling on an urban rail transit line. Engineering 12, 202–220.
Luan, X., Corman, F., 2022. Passenger-oriented traffic control for rail networks: an optimization model considering crowding effects on passenger choices and train operations. Transport. Res. Part B: Methodol. 158, 239–272.
Luan, X., Wang, Y., De Schutter, B., Meng, L., Lodewijks, G., Corman, F., 2018. Integration of real-time traffic management and train control for rail networks-part 1: Optimization problems and solution approaches. Transport. Res. Part B: Methodol. 115, 41–71.
Marra, A.D., Corman, F., 2023. How different network disturbances affect route choice of public transport passengers. A descriptive study based on tracking. Exp. Syst. Appl. 213, 119083.
Meloni, C., Pranzo, M., Samà, M., 2021. Risk of delay evaluation in real-time train scheduling with uncertain dwell times. Transport. Res. Part E: Logist. Transport. Rev. 152, 102366.
Meng, L., Zhou, X., 2011. Robust single-track train dispatching model under a dynamic and stochastic environment: a scenario-based rolling horizon solution approach. Transport. Res. Part B: Methodol. 45 (7), 1080–1102.
Meng, L., Luan, X., Zhou, X., 2016. A train dispatching model under a stochastic environment: stable train routing constraints and reformulation. Netw. Spat. Econ. 16, 791–820.
Mo, B., Koutsopoulos, H. N., Shen, Z. J. M., Zhao, J., 2023b. Individual Path Recommendation Under Public Transit Service Disruptions Considering Behavior Uncertainty. arXiv preprint arXiv:2301.00916.
Mo, B., Koutsopoulos, H.N., Zhao, J., 2022. Inferring passenger responses to urban rail disruptions using smart card data: a probabilistic framework. Transport. Res. Part E: Logist. Transport. Rev. 159, 102628.
Mo, B., Koutsopoulos, H.N., Shen, Z.J.M., Zhao, J., 2023a. Robust path recommendations during public transit disruptions under demand uncertainty. Transport. Res. Part B: Methodol. 169, 82–107.
Moaveni, B., Najafi, S., 2017. Metro traffic modeling and regulation in loop lines using a robust model predictive controller to improve passenger satisfaction. IEEE Trans. Control Syst. Technol. 26 (5), 1541–1551.
Parbo, J., Nielsen, O.A., Prato, C.G., 2016. Passenger perspectives in railway timetabling: a literature review. Transp. Rev. 36 (4), 500–526.
Pellegrini, P., Marlière, G., Rodriguez, J., 2014. Optimal train routing and scheduling for managing traffic perturbations in complex junctions. Transport. Res. Part B: Methodol. 59, 58–80.
Pellegrini, P., Marlière, G., Rodriguez, J., 2016. A detailed analysis of the actual impact of real-time railway traffic management optimization. J. Rail Transp. Plann. Manage. 6 (1), 13–31.
Peng, S., Yang, X., Ding, S., Wu, J., Sun, H., 2023. A dynamic rescheduling and speed management approach for high-speed trains with uncertain time-delay. Inf. Sci. 632, 201–220.
Powell, W.B., 2022. Reinforcement Learning and Stochastic Optimization: A Unified Framework for Sequential Decisions. John Wiley & Sons.
Quaglietta, E., Corman, F., Goverde, R.M., 2013. Stability analysis of railway dispatching plans in a stochastic and dynamic environment. J. Rail Transp. Plann. Manage. 3 (4), 137–149.
Reynolds, E., Maher, S.J., 2022. A data-driven, variable-speed model for the train timetable rescheduling problem. Comput. Oper. Res. 142, 105719.
Samà, M., Pellegrini, P., D'Ariano, A., Rodriguez, J., Pacciarelli, D., 2016. Ant colony optimization for the real-time train routing selection problem. Transport. Res. Part B: Methodol. 85, 89–108.
Samà, M., Corman, F., Pacciarelli, D., 2017. A variable neighbourhood search for fast train scheduling and routing during disturbed railway traffic situations. Comput. Oper. Res. 78, 480–499.
Schön, C., König, E., 2018. A stochastic dynamic programming approach for delay management of a single train line. Eur. J. Oper. Res. 271 (2), 501–518.
Shakibayifar, M., Hassannayebi, E., Jafary, H., Sajedinejad, A., 2017. Stochastic optimization of an urban rail timetable under time-dependent and uncertain demand. Appl. Stoch. Model. Bus. Ind. 33 (6), 640–661.
Shakibayifar, M., Sheikholeslami, A., Corman, F., 2018. A simulation-based optimization approach to reschedule train traffic in uncertain conditions during disruptions. Sci. Iran. 25 (2), 646–662.
Sharma, B., Pellegrini, P., Rodriguez, J., Chaudhary, N., 2023. A review of passenger-oriented railway rescheduling approaches. Eur. Transp. Res. Rev. 15 (1), 14.

Solinen, E., Nicholson, G., Peterson, A., 2017. A microscopic evaluation of railway timetable robustness and critical points. J. Rail Transp. Plann. Manage. 7 (4), 207–223.
Spanninger, T., Wiedemann, N., Corman, F., 2023. Quantifying the dynamic predictability of train delay with uncertainty-aware neural networks. Transport. Res. Part C: Emerg. Technol. (submitted).
Tumeo, M.A., 1994. The meaning of stochasticity, randomness and uncertainty in environmental modeling. In: Hipel, K.W. (Ed.) Stochastic and Statistical Methods in Hydrology and Environmental Engineering. Water Science and Technology Library, vol 10/4. Springer, Dordrecht. https://doi-org.ezproxy.is.ed.ac.uk/10.1007/978-94-011-1072-3_3.
Van Der Hurk, E., Kroon, L., Maróti, G., Vervest, P., 2014. Deduction of passengers' route choices from smart card data. IEEE Trans. Intell. Transp. Syst. 16 (1), 430–440.
Van der Hurk, E., Kroon, L., Maróti, G., 2018. Passenger advice and rolling stock rescheduling under uncertainty for disruption management. Transp. Sci. 52 (6), 1391–1411.
Van Thielen, S., Corman, F., Vansteenwegen, P., 2018. Considering a dynamic impact zone for real-time railway traffic management. Transport. Res. Part B: Methodol. 111, 39–59.
Van Thielen, S., Corman, F., Vansteenwegen, P., 2019. Towards a conflict prevention strategy applicable for real-time railway traffic management. J. Rail Transp. Plann. Manage. 11, 100139.
Veelenturf, L.P., Kidd, M.P., Cacchiani, V., Kroon, L.G., Toth, P., 2016. A railway timetable rescheduling approach for handling large-scale disruptions. Transp. Sci. 50 (3), 841–862.
Veelenturf, L.P., Kroon, L.G., Maróti, G., 2017. Passenger oriented railway disruption management by adapting timetables and rolling stock schedules. Transport. Res. Part C: Emerg. Technol. 80, 133–147.
Wang, X., Su, S., Cao, Y., Wang, X., 2022. Robust control for dynamic train regulation in fully automatic operation system under uncertain wireless transmissions. IEEE Trans. Intell. Transp. Syst. 23 (11), 20721–20734.
Wang, P., Trivella, A., Goverde, R.M., Corman, F., 2020. Train trajectory optimization for improved on-time arrival under parametric uncertainty. Transport. Res. Part C: Emerg. Technol. 119, 102680.
Wen, C., Huang, P., Li, Z., Lessan, J., Fu, L., Jiang, C., Xu, X., 2019. Train dispatching management with data-driven approaches: a comprehensive review and appraisal. IEEE Access 7, 114547–114571.
Xie, J., Wong, S.C., Zhan, S., Lo, S.M., Chen, A., 2020. Train schedule optimization based on schedule-based stochastic passenger assignment. Transport. Res. Part E: Logist. Transport. Rev. 136, 101882.
Xu, P., Corman, F., Peng, Q., 2016. Analyzing railway disruptions and their impact on delayed traffic in Chinese high-speed railway. IFAC-PapersOnLine 49 (3), 84–89.
Xu, P., Corman, F., Peng, Q., Luan, X., 2017. A train rescheduling model integrating speed management during disruptions of high-speed traffic under a quasi-moving block system. Transport. Res. Part B: Methodol. 104, 638–666.
Xu, L., Ng, T.S.A., 2020. A robust mixed-integer linear programming model for mitigating rail transit disruptions under uncertainty. Transp. Sci. 54 (5), 1388–1407.
Xu, L., Ng, T.S., Costa, A., 2021. Optimizing disruption tolerance for rail transit networks under uncertainty. Transp. Sci. 55 (5), 1206–1225.
Yang, L., Zhou, X., Gao, Z., 2013. Rescheduling trains with scenario-based fuzzy recovery time representation on two-way double-track railways. Soft. Comput. 17, 605–616.
Yang, L., Zhou, X., Gao, Z., 2014. Credibility-based rescheduling model in a double-track railway network: a fuzzy reliable optimization approach. Omega 48, 75–93.
Yap, M., Cats, O., 2019. Analysis and prediction of disruptions in metro networks. In 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). IEEE, Cracow, pp. 1–7.
Yin, J., Chen, D., Yang, L., Tang, T., Ran, B., 2015. Efficient real-time train operation algorithms with uncertain passenger demands. IEEE Trans. Intell. Transp. Syst. 17 (9), 2600–2612.
Yin, J., Tang, T., Yang, L., Gao, Z., Ran, B., 2016. Energy-efficient metro train rescheduling with uncertain time-variant passenger demands: an approximate dynamic programming approach. Transport. Res. Part B: Methodol. 91, 178–210.
Yin, J., Yang, L., D'Ariano, A., Tang, T., Gao, Z., 2022. Integrated backup rolling stock allocation and timetable rescheduling with uncertain time-variant passenger demand under disruptive events. INFORMS J. Comput. 34 (6), 3234–3258.
Zhan, S., Kroon, L.G., Veelenturf, L.P., Wagenaar, J.C., 2015. Real-time high-speed train rescheduling in case of a complete blockage. Transport. Res. Part B: Methodol. 78, 182–201.
Zhan, S., Kroon, L.G., Zhao, J., Peng, Q., 2016. A rolling horizon approach to the high speed train rescheduling problem in case of a partial segment blockage. Transport. Res. Part E: Logist. Transport. Rev. 95, 32–61.
Zhan, S., Wong, S.C., Shang, P., Peng, Q., Xie, J., Lo, S.M., 2021. Integrated railway timetable rescheduling and dynamic passenger routing during a complete blockage. Transport. Res. Part B: Methodol. 143, 86–123.
Zhan, S., Wang, P., Wong, S.C., Lo, S.M., 2022a. Energy-efficient high-speed train rescheduling during a major disruption. Transport. Res. Part E: Logist. Transport. Rev. 157, 102492.
Zhan, S., Wong, S.C., Shang, P., Lo, S.M., 2022b. Train rescheduling in a major disruption on a high-speed railway network with seat reservation. Transportmet. A: Transport Sci. 18 (3), 532–567.
Zhang, C., Gao, Y., Cacchiani, V., Yang, L., Gao, Z., 2023. Train rescheduling for large-scale disruptions in a large-scale railway network. Transport. Res. Part B: Methodol. 174, 102786.
Zhang, H., Li, S., Wang, Y., Wang, Y., Yang, L., 2021. Real-time optimization strategy for single-track high-speed train rescheduling with disturbance uncertainties: a scenario-based chance-constrained model predictive control approach. Comput. Oper. Res. 127, 105135.
Zhu, Y., Goverde, R.M., 2019. Dynamic passenger assignment for major railway disruptions considering information interventions. Netw. Spat. Econ. 19 (4), 1249–1279.
Zhu, Y., Goverde, R.M., 2020a. Integrated timetable rescheduling and passenger reassignment during railway disruptions. Transport. Res. Part B: Methodol. 140, 282–314.
Zhu, Y., Goverde, R.M., 2020b. Dynamic and robust timetable rescheduling for uncertain railway disruptions. J. Rail Transp. Plann. Manage. 15, 100196.
Zilko, A.A., Kurowicka, D., Goverde, R.M., 2016. Modeling railway disruption lengths with Copula Bayesian Networks. Transport. Res. Part C: Emerg. Technol. 68, 350–368.