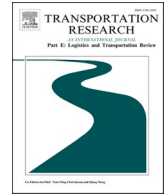




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Transportation Research Part E

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

At-stop control measures in public transport: Literature review and research agenda

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ARTICLE INFO

Keywords:

Public transport
Control
Service reliability
Holding
Rescheduling
Stop-skipping

ABSTRACT

In this literature review, we systematically review studies on public transit control with a specific focus on at-stop measures. In our synthesis of the relevant literature, we consider three perspectives: (1) the mathematical models of the proposed methodologies; (2) their complexity; (3) their applicability in real-time operations and their advantages and disadvantages considering their practical implications. The reviewed control methods include holding, dynamic dispatching, and stop-skipping. Control methods, that have attracted more attention in recent years due to the advancements in automation and data availability, aim at alleviating the negative effects of service variability because of external disruptions. Following the synthesis of the literature, we propose a research agenda pertaining to the combination of control measures, passenger-oriented decision making, coordinated network control, deployment of electric buses and disturbance management.

1. Introduction

Decisions regarding the operations of transit services are made at different planning stages. At the strategic level, a set of stops and a set of lines that serve these stops are determined as part of the network design step (Kepaptsoglou and Karlaftis, 2009a). At the tactical planning stage, one has to determine the frequency, the timetable, and the crew and vehicle schedules of each service line (Wren and Rousseau, 1995; Gintner et al., 2005; Kliewer et al., 2006; Yu et al., 2009; Sun et al., 2015; Wu et al., 2016). Tactical plans are communicated well in advance, and all stakeholders (i.e., public transport authorities/operators, drivers, passengers) are aware of them prior to the start of the daily operations (Ceder, 2007). At the operational stage, which is the focus of this study, dynamic control approaches such as holding, rescheduling or stop-skipping are frequently deployed to react to disturbances and disruptions in real-time.

Dynamic control is needed in transit operations to alleviate the adverse effects of bunching, overcrowding and schedule sliding (note that schedule sliding refers to the case where vehicles cannot be dispatched according to the planned timetable because they accumulated delays when performing previous trips). This is particularly relevant for public transport services that operate in mixed-traffic and are therefore subject to greater uncertainty. Bus and tram services are often subject to recurrent disturbances due to the inherently uncertain operational environment. Variations in system operations are typically caused by interactions with mixed traffic, traffic signals, limited stop capacity, passenger demand variability and driver behavior. Such variations call for the deployment of

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<https://doi.org/10.1016/j.tre.2020.102176>

Received 30 April 2020; Received in revised form 14 October 2020; Accepted 20 November 2020

Available online 10 December 2020

1366-5545/© 2020 The Author(s).

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correcting control measures aimed at improving service reliability. Moreover, bus and tram (or, more generally, at-grade urban rail transit) services offer a relatively high degree of freedom in their operations (e.g., they are not dominated by safety considerations enforced through the blocking and signaling traffic regime characteristics of heavy rail operations). Exploiting this higher degree of freedom, operational control measures can be used to mitigate bunching, schedule sliding and overcrowding that occur due to the spatio-temporal variation of travel times and passenger demand (Abkowitz and Tozzi, 1987; Clotfelter, 1993; Strathman et al., 1999; Hans et al., 2015a; Hans et al., 2015b).

Alleviating bunching, overcrowding, and the sliding of schedules is a fundamental objective of advanced transit management systems. However, given that the cause of such phenomena is the stochastic nature of inter-station travel times and passenger demand, solving such problems at the strategic or the tactical planning level is not suitable (Gkiotsalitis and Alesiani, 2019). Therefore, real-time “corrective” control measures are needed to react continuously to the travel time and passenger demand variations. Consequently, there is an upsurge in research and development in this field which is supported by the recent technological advances and the high penetration rates of telematics that produce automated vehicle location (AVL) data, automatic passenger counting (APC) data, and automated fare collection (AFC) data.

Data availability is not only instrumental in observing service operations and performing corrective actions in real-time, but it also offers a monitoring tool to the transport authorities to oversee and assess the transit services. This has strong implications and has resulted in new business models where transport authorities provide monetary incentives to operators that perform well (and vice versa). For instance, the Land Transport Authority (LTA) in Singapore offers 6,000 Singaporean dollars for each 0.1-min improvement of the excessive passenger waiting times (Leong et al., 2016). Consequently, the data availability that enables the monitoring of the transit operations has brought new challenges to the transit service provider which bears the responsibility of ensuring a seamless service. In this context, service management teams have started to exercise real-time control measures to improve their services (Trompet et al., 2011). Do, however, real-time control measures always improve the operational and passenger-related costs? Are the costs for external actors acceptable? Is it possible to develop models that provide an accurate representation of reality that can also be solved in real-time in order to obtain appropriate control measures?

Two strands of research have tried to answer the aforementioned questions by adopting distinctive approaches. One strand attempts to incorporate the stochastic nature of travel times and passenger demand into the dynamic control formulation, e.g., Hickman (2001), Berrebi et al. (2015). The alternative approach aims to limit the stochastic elements of the travel times and passenger demand by solving deterministic optimization problems in very short time-horizons, e.g., Eberlein et al. (2001). The actual performance of the selected control measures, independent of which strand is chosen, depends on the travel time and passenger demand variability levels which are often case study-specific.

Developing real-time control methods for public transport service operations has been the focus of numerous research papers over the past few years. Collectively, the related literature provides compelling evidence supporting the implementation of real-time control measures, notwithstanding the negative effect(s) of each measure. In addition, the application of real-time control measures does not always guarantee the improvement of operations. Evidence from the related literature shows that if the travel time and passenger demand estimates are unreliable, the suggested control measures might yield a negative impact (see Fu and Yang (2002)). In addition, little is known about whether the inclusion of classic traffic theory models into vehicle control methods can limit the unpredictability of inter-station travel times and increase the chances of achieving improved operations (Chow et al., 2017; Sirmatel and Geroliminis, 2018).

This paper reviews and synthesizes works that cover the aforementioned research areas. Through a systematic literature review, we perform a comprehensive search of related works, identify conflicting research, and discuss the conditions under which one method is expected to perform better than another. In this review we seek to answer the following questions:

- what are the side-effects of common real-time control methods?
- what is the potential of combining different real-time control methods?
- what are the most common models for analyzing the different real-time control methods? do they offer an accurate representation of reality and can they be efficiently solved (i.e., to global optimality) in real-time?
- what are the most common solution methods and their properties?
- what are the most pressing and promising directions for future research?

The remainder of this paper is structured as follows. In Section 2, we provide a general overview of common control methods for public transport operations. In Section 3, we review and synthesize the works on vehicle holding. In Section 4, we review the works on rescheduling. In Section 5, we review the works on stop-skipping and mixed control approaches that integrate stop-skipping with holding or short-turning. In Section 7, we propose a research agenda consisting of five themes addressing key challenges. Finally, in Section 7 we conclude the paper and provide future research directions.

2. An overview of control measures

Common corrective actions during daily operations include stop-skipping (Sun and Hickman, 2005; Chen et al., 2015c; Yu et al., 2015; Liu et al., 2013), vehicle holding at specific stops (Newell, 1974; Berrebi et al., 2015; Hernández et al., 2015; Wu et al., 2017; Gavriilidou and Cats, 2018) or rescheduling (Adamski and Turnau, 1998; Strathman et al., 1999). A distinct line of works tried to combine stop-skipping and vehicle holding (Eberlein, 1995; Lin et al., 1995; Cortés et al., 2010; Sáez et al., 2012). In addition, Gkiotsalitis et al. (2019b) proposed combining short-turning and interlining options using the concept of virtual lines. Muñoz et al.

(2013) intertwined speed control with vehicle holding. Lastly, Cortés et al. (2011) integrated short turning and deadheading. Despite the above, given the computational complexity of each problem and the requirement of computing an optimal control strategy in quasi-real-time, different operational control approaches are typically applied in isolation.

Apart from holding, rescheduling and stop-skipping, inter-station control can also be an option. Typical inter-station control strategies are traffic signal priority (Skabardonis, 2000; Liu et al., 2003; Koehler and Kraus, 2010; van Oort et al., 2012) and speed control (Daganzo and Pilachowski, 2011; Muñoz et al., 2013; Wang et al., 2014; Ampountolas and Kring, 2015). We note though that inter-station control strategies have received relatively little attention in the public transport literature compared to holding, rescheduling and stop-skipping methods. Therefore, they will be treated as an extension of at-stop control measures in this literature review.

Considering holding, stop-skipping and rescheduling, we note that each control method has its own adverse effects. Stop-skipping increases the inconvenience of passengers who cannot board the vehicle that skips their stop (Fu et al., 2003; Liu et al., 2013). Holding increases the trip's travel time and the inconvenience of onboard passengers who wait while the vehicle is held at the stop(s) (Fu and Yang, 2002). Finally, rescheduling can affect the crew/vehicle schedules and can result in schedule sliding.

For control strategies to be effective it is essential that their implementation is integrated into service operations and that both drivers and passengers find it acceptable. All control strategies involve inducing delays for some travelers at the interest of overall system performance. Many services will be reluctant to adopt any strategy that involves preventing passengers from boarding a vehicle, such as stop-skipping and limited boarding. This is one of the reasons why holding strategies are more commonly applied. Holding a vehicle briefly at a stop is tolerated and speed adjustments and traffic signal priority can also contribute to reducing the holding time required by distributing it over different parts of the vehicle trajectory.

For any control strategy to be effective, it needs to be acted upon by drivers. Simulation studies have shown that cooperative fleet control strategies such as even-headway holding (i.e. equalizing the headway from the backward and forward vehicles) are highly robust to the impacts of imperfect driver compliance (Cats et al., 2012; Phillips et al., 2015) as well as imprecise communication with the driver display (Cats et al., 2012).

Field implementations provide insights on the key success factors in the implementation of control strategies. Most of which were realized in restrictive contexts where a full-fledged cooperative system was not available. Field pilots that relied on street supervisors and dedicated control center dispatchers have proven to be of limited success due to the prohibitive workload and the limited responsiveness such settings provide (Pangilinan et al., 2008; Soza-Parra et al., 2019). Small-scale trials where tablets were provided to either drivers or terminal personnel had also embedded insufficiently the control in daily operations and reported difficulties with technical failures and drivers' compliance (Lizana et al., 2014; Fabian et al., 2018). Both latter issues were also mentioned by (Berrebi et al., 2018a) for two small-scale pilots. This highlights the importance of integrating the control instructions into computer displays and having all vehicles equipped with those as is the case in the control implemented in Stockholm (Cats, 2014). Interestingly, an analysis of bus drivers' heart rate accompanied by a mental workload questionnaire revealed that, everything else being the same, driving with a cooperative control strategy resulted in much lower stress levels (Hlotova et al., 2014). This is also, to the best of our knowledge, the only case where cooperative control strategies have become the state-of-the-practice starting in 2014.

In addition to technical considerations, experiences gained in the aforementioned cases, also highlight the importance of the human factor in designing control schemes. Empirical analysis of vehicle movement data has shown that drivers' behavior and heterogeneity have a considerable impact on service reliability (Strathman et al., 2002; Mishalani et al., 2008). Moreover, there is evidence that drivers adjust their speeds in response to real-time guidance and that this response depends on where performance is measured (Cats, 2019). This means that to be effective, it is essential to devise incentives that are easy to understand and communicate, consistent and transparent throughout the service chain - from drivers to control center dispatchers and management (Cats, 2014).

In terms of key performance indicators, the main challenge in high-frequency services is to maintain the planned headways between vehicles at each stop, whereas in low-frequency services it is to adhere to the scheduled departure times from stops (Trompet et al., 2009; Randall et al., 2007; Trompet et al., 2011; Cats, 2014). If the demand and the travel times of all vehicle trips that operate in a service line are equal and stable, vehicle trips will maintain an even headway at all downstream stops. This will result in a regular service where the actual waiting times at stops meet the passengers' expectations. Nevertheless, travel time and passenger demand variations during the actual operations result in unreliable and inconsistent services (Chen et al., 2009; Daganzo, 2009). Knoppers and Muller (1995, 2018b) and Knoppers and Muller (1995) have shown that the fixed service intervals cannot be maintained at all stops. Indeed, even if vehicles are dispatched according to their planned headways, their headways are expected to deviate from their scheduled values as they move towards downstream stops (Hans et al., 2015b).

To address the adverse effects of the demand and travel time variability, several periodic optimization approaches have emerged over the past 40 years. Periodic optimization approaches of fleet operations consider multiple decision variables and are based on iterative, finite-horizon optimization(s) of fleet operations. At time t , the current state of the fleet operations (i.e., current positions of running trips) is used as input and, together with the expected travel times within a relatively short time horizon $t + T$, the control measures (i.e., holding, stop-skipping, rescheduling) of multiple trips are determined. We note here that there are two main issues with the periodic optimization methods:

- if the number of vehicle trips, $i = \{1, 2, \dots\}$, that belong to the periodic optimization time period $t + T$ is too big, determining the appropriate control measures of all those trips results in complex, multi-variable optimization problems that cannot be solved in real-time (Sánchez-Martínez et al., 2016). Additionally, as in model predictive control (MDP), the control measures of multiple trips will be updated before we even have the chance to implement them in practice because of the continuous updates of the operational status (Nikolaou, 2001);

- if the optimization horizon is too short and only one trip at a time is controlled, the decisions are myopic. Hence, the performance of one selected trip might be improved, but the performance of the overall operations (Eberlein et al., 2001).

When defining the control measures of fleet operations in real-time, a balance should be established between considering multiple future trips or focusing on one trip at a time. This is prevalent in the literature review of holding, rescheduling, and stop-skipping methods that is presented in the following sections. Finally, because the focus of this literature review is on mathematical models for real-time control, we briefly present some basic terminology with regards to mathematical optimization in Appendix A.

3. Holding

Control methods for vehicle holding have been studied since the early 1970s (see Osuna and Newell, 1972; Newell, 1974). Nevertheless, the holding problem remains a prominent research topic because of its inherent complexity. Newell (1974) considered only one time point at which vehicles can be intentionally delayed, and devised a strategy for holding a vehicle to minimize the average waiting time of the passengers. Time points are defined in the literature as stops where vehicles that arrive before the scheduled departure time must wait to depart on time (see Klumpenhower and Wirasinghe, 2018). Determining the optimal number and the optimal locations of time points is addressed by a number of works in past literature. Klumpenhower and Wirasinghe (2018) developed a Markov Chain model to accurately capture the stochastic nature of a bus trajectory as the bus moves along a route in mixed traffic. Then, Klumpenhower and Wirasinghe (2018) performed a theoretical analysis of routes demonstrating where problem points may exist in order to establish time points. Fu and Yang (2002) performed several simulations considering different time point stops and showed that the holding is more effective if it is applied at time points with higher boarding demand. In addition, Fu and Yang (2002) investigated the effect of the number of time point stops testing the one-stop control, two-stop control, and all-stop control. Based on their simulations, they concluded that a targeted two-stop control is an acceptable option. Finally, Cats et al. (2014) determined both the optimal number and optimal location of the time point stops where holding takes place, and assessed their impacts on transit performance using simulation.

Typical objectives of holding methods are headway adherence to the schedule (Rossetti and Turitto, 1998; Gkiotsalitis and Cats, 2019), headway regularity (Bartholdi and Eisenstein, 2012; Daganzo, 2009; Cats et al., 2011), and the minimization of passenger waiting and in-vehicle times (Delgado et al., 2009; Delgado et al., 2012; Sáez et al., 2012). It should be noted here that, as a general practice, vehicles are not held at every stop because this will increase the passenger inconvenience. In contrast, as discussed above, vehicle holding is only allowed at a pre-determined sub-set of important stops, known as intermediate time points (ITPs).

In vehicle holding, two different directions of research have emerged. One direction models the vehicle holding problem as a periodic optimization, rolling horizon problem where decisions about the holding times concern the entirety of trips that will operate in a short horizon, $t + T$. To achieve that, information about the current trajectories of vehicle trips and their predicted values in the near future is incorporated in the respective mathematical programs (Eberlein et al., 2001). In this line of research, the holding problem is typically modeled as a mathematical program with multiple decision variables, and collective decisions are made.

The second direction of research determines the holding time of a single trip when it arrives at a time point stop. Because every time they decide the holding time of a single trip, such approaches yield single-variable optimization problems. Single-variable optimization problems lead to closed-form expressions that can determine the holding time of a trip in real-time without the need of solving a complex mathematical program (Hickman, 2001; Fu and Yang, 2002; Van Oort et al., 2010). With such approaches, the holding time

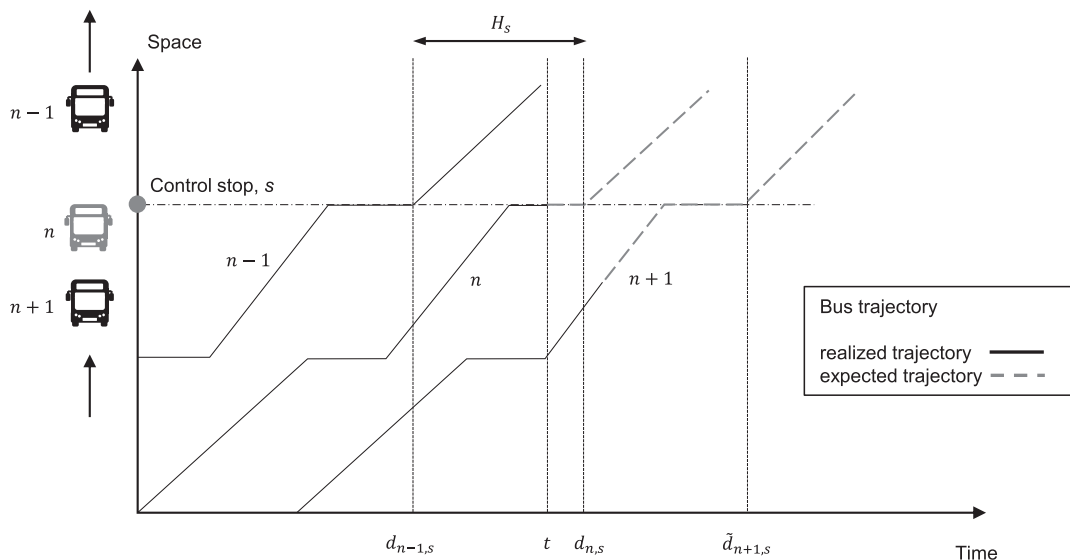


Fig. 1. Time-space diagram of the realized and expected trajectories of three successive vehicle trips.

decision of a trip n is typically made when it arrives at a time point stop s based on:

- its actual time headway with its preceding trip, $n - 1$, (one-headway-based control logic)
- its actual time headway with its preceding trip, $n - 1$, and its expected time headway with its following trip, $n + 1$, (two-headway-based control logic)

This can be understood with the use of the time–space diagram of Fig. 1, where:

- H_s is the target headway (i.e., scheduled headway that we need to adhere to),
- t the time when trip n has completed all its boardings/alightings at stop s and is ready to depart (in case no holding is applied),
- $d_{n-1,s}$ the actual departure time of trip $n - 1$ from stop s ,
- $d_{n,s}$ the optimized departure time of trip n from stop s ,
- $\tilde{d}_{n+1,s}$ the expected departure time of trip $n + 1$ from stop s ,
- $(d_{n,s} - t)$ the decided holding time of trip n at stop s .

In the one-headway-based control logic, the holding time of trip n when it arrives at stop s depends on the target headway, H_s , the time when it finishes its boardings/alightings and is ready to depart, t , and the departure time of its preceding trip from stop s , $d_{n-1,s}$. A simple closed-form expression that can determine the holding time $h_{n,s}$ of trip n at stop s is:

$$h_{n,s} = \begin{cases} 0 & \text{if } t - d_{n-1,s} \geq H_s \\ H_s - (t - d_{n-1,s}) & \text{otherwise.} \end{cases} \quad (1)$$

This simple closed-form expression allows vehicle n to depart immediately after finishing its boardings/alightings (no holding) if $t - d_{n-1,s} \geq H_s$ which indicates that trip n is behind schedule and needs to catch up with its preceding trip. If it is not behind, it is held at stop s for time $H_s - (t - d_{n-1,s})$ to meet again the target headway. Given that holding trip n for time $H_s - (t - d_{n-1,s})$ might not always be desirable because it increases the travel time of trip n , a weight $0 \leq a \leq 1$ can be applied to $H_s - (t - d_{n-1,s})$ resulting in $a(H_s - (t - d_{n-1,s}))$. Intuitively, if $a = 0$ vehicle n is never held, whereas if $a = 1$ vehicle n is held for time $H_s - (t - d_{n-1,s})$ to adhere again to the target headway. Any other value of a in the range $[0, 1]$ determines the strength of the holding control. The value of a depends on the preferences of the service operator because some operators might be more willing to hold their vehicles at stops for a prolonged time in order to adhere to the scheduled headways, whereas other operators might not. Fu and Yang (2002) performed a sensitivity analysis testing different values of a and concluded that tighter control can reduce the average passenger wait time by up to 24%. At the same time, tighter control increases the total trip travel time and triggers a holding action more often. In more detail, full control ($a = 1$) resulted in 90% of vehicles being held when arriving at a time point, whereas lower control strengths in the range of 0–0.6 resulted in implementing control decisions on up to 74% of the vehicles.

The aforementioned one-headway-based control logic can be expanded into a two-headway-based control logic that considers also the expected departure time of the following trip $n + 1$ at stop s , $\tilde{d}_{n+1,s}$. For instance, a two-headway-based control logic can be expressed as follows:

Algorithm 1. Two-headway-based holding control logic (Fu and Yang, 2002)

In the remainder of this section, we discuss the past literature on the multi-variable vehicle holding optimization approaches and the single-variable optimization approaches (sub-Sections 3.1.1 and 3.1.2). In 3.1 and 3.2, a distinction is made between approaches that consider the vehicle capacity in the optimization process and the ones that do not.

3.1. Holding without considering the vehicle capacity

We hereby discuss the main multi-variable and single-variable vehicle holding optimization methods that do not consider the vehicle capacity limits in the optimization process. Multi-variable holding approaches that try to determine the holding times of multiple vehicle trips might not be able to provide a solution in real-time due to the complexity of the respective mathematical programs. For this reason, we report past works on multi-variable and single-variable mathematical optimization in the separate Sections 3.1.1 and 3.1.2.

3.1.1. Multi-variable mathematical programs

Examples of multi-variable holding optimization methods are the periodic optimization mathematical programs of Eberlein (1995), Eberlein et al. (2001), Shen and Wilson (2001), Sánchez-Martínez et al. (2016). Such mathematical programs simultaneously determine the holding times of all vehicles that are expected to operate within a rolling horizon. The optimized holding times are updated in rolled rolling horizons when new information becomes available.

Eberlein et al. (2001) considered real-time information and assumed that travel times and passenger arrival rates remain constant in rolling horizons with short time duration. The holding problem of all running vehicles was modeled as a quadratic program that minimizes the total passenger waiting times. Zolfaghari et al. (2004) developed a mathematical control model for holding using real-time information about the locations of vehicles along a specified route and the resulting mathematical program was solved with

metaheuristics (specifically, simulated annealing). Gkiotsalitis and Cats (2019) used alternating optimization and branch and bound to determine the holding times of multiple trips in a rolling horizon. Sun and Hickman (2004) discretized the holding times by allowing 5-s increments and returned a solution with simple enumeration. Later, Sun and Hickman (2008) formulated the holding problem considering the passenger waiting times and in-vehicle delays as a convex quadratic programming problem and used a decomposition-based heuristic for its solution. The effectiveness of the heuristic was tested in a hypothetical numerical example.

More recently, Alesiani and Gkiotsalitis (2018) and Wang and Sun (2020) followed a different approach that used reinforcement learning to determine the holding times of multiple trips instead of solving a mathematical program. By using reinforcement learning, the running vehicles are modeled as agents and a headway-oriented reward function is defined to explore the effects of potential holding strategies.

Most of the above-mentioned models resort to heuristics to solve the mathematical programs due to the complexity of the formulations and the non-polynomial computational costs. Typically, models solved with exact methods exhibit scalability issues when the number of problem variables increases, whereas models solved with heuristics result in large optimality gaps.

3.1.2. Single-variable approaches: rule-based methods and analytic solutions

In this sub-section, we report works that determine the holding time of a single vehicle at a time and do not consider the vehicle capacity in the optimization process. Fu and Yang (2002) tested two of the most common rule-based holding strategies: (i) the one-headway-based control where a vehicle is held at a time point stop if its time headway with its preceding vehicle is lower than a pre-defined threshold; and (ii) the two-headway-based control that considers the time headway of a vehicle with its preceding and following vehicle. Bellei and Gkoumas (2009) proposed also threshold-based and information-based vehicle holding considering the inherent uncertainty of transit operation because of the random travel times and passenger arrivals at stops.

Xuan et al. (2011) proposed a simple control strategy that has a closed-form expression for holding one trip at a time. We also report the works of Daganzo and Pilachowski (2011, 2020), even if their focus was on speed control. Daganzo and Pilachowski (2011) and Ampountolas and Kring (2020) proposed an adaptive control scheme that adjusts a vehicle cruising speed in real-time based on both its front and rear spacings. In line with other closed-form approaches, the work of Daganzo and Pilachowski (2011) had a simple and decentralized logic enabling to correct the effect of traffic disruptions in real-time.

Bartholdi and Eisenstein (2012) proposed an analytic holding solution which changes the headway of each newly arrived vehicle at a stop to the weighted average of its former headway and that of the trailing vehicle. This approach tends to re-equalize the headways after any disturbance. Its major difference from other works is that its objective is to maintain headway regularity and not to adhere to a scheduled (target) headway. Thus, a rule-based headway threshold is not triggering the holding. Instead, the holding decisions constantly adjust and re-equalize the headways.

Berrebi et al. (2015, 2018b) proposed a method consisting of identifying probabilistically the vehicle that will arrive the latest at a particular point. Then, each preceding vehicle is held to prevent the building up of a large gap for the lagging vehicle. Van Oort et al. (2010) also tested schedule-based and headway-based holding strategies where the solution was expressed as a closed-form expression of arrival times and scheduled headways. They tested the importance of setting a maximum holding time and a reliability buffer time in tram line 9 in The Hague.

Wu et al. (2017) incorporated the passenger demand into the estimation of vehicle trajectories and addressed the single-variable holding problem with the use of the one-headway-based holding logic. In the one-headway-based holding of Wu et al. (2017), a vehicle is held if the headway with its preceding vehicle is less than the scheduled headway - otherwise, it is dispatched immediately. Although Wu et al. (2017) incorporate the demand and the capacity of vehicles into the calculation of vehicle dwell times, the objective of the simplistic, one-headway-based control logic does not consider the improvement of vehicle loads and focuses merely on service regularity. For this reason, this study is assigned to the category of studies that do not use the violation of capacity limits as an optimization objective.

Hickman (2001) used the stochastic model developed by Marguier (1985) to derive the trajectories of vehicles on a single route. Using Marguier's model, Hickman (2001) developed a holding algorithm that is applied each time a vehicle arrives at the time point stop. To this end, Marguier's model was used to approximate the trajectories of all upstream vehicles. The optimal holding time was computed using a line search solution method because obtaining an analytic solution was not possible given the complexity of deriving the first-order conditions of the optimization problem. Recently, holding control has also been integrated with transit signal priority (TSP) with the use of rule-based holding criteria (Laskaris et al., 2020).

3.2. Holding Methods that consider the vehicle capacity limits

Previously, we reviewed holding methods that do not account for passenger demand and vehicle capacity limitations in the optimization process. In this sub-section, we review past works that consider the capacity limitations in the optimization process. Although we do not focus on rail operations, we note here the work of Puong and Wilson (2008) who developed a mixed-integer program for holding trains whilst considering capacity limitations.

Sánchez-Martínez et al. (2016) formulated a mathematical model to produce a plan of holding times for all running vehicles in a rolling horizon that caters for passenger demand. Its effectiveness was evaluated within a simulation environment. The objective function in that model was not convex and did not allow the derivation of an analytic solution. Instead, Sánchez-Martínez et al. (2016) employed the optimization algorithm of Powell (2009) to derive local minima of the nonlinear objective function. Computational times were also prohibitive for instances with many time points and a large fleet size.

Delgado et al. (2009) developed a mathematical program that incorporates vehicle-capacity constraints. As in Sánchez-Martínez

et al. (2016), they calculated the holding times of all vehicles in a rolling horizon resulting in a multi-variable decision problem. In a later work, Delgado et al. (2012) also addressed the problem of determining the holding times of all running vehicles in a rolling horizon. Their objective was to minimize the total times experienced by all passengers in the system resulting in a non-convex, nonlinear objective function that cannot be (always) solved to global optimality. Then, they performed a simulation-based evaluation of two control policies applied within a rolling horizon framework: (i) vehicle holding that does not consider boarding limits, and (ii) holding combined with boarding limits, in which the number of boarding passengers at any stop can be limited. The respective mathematical programs were solved using MINOS as an optimization solver, similarly to the work of Hernández et al. (2015).

Sáez et al. (2012) proposed a hybrid control approach for both holding and stop-skipping resulting in a mixed-integer non-linear program. Sáez et al. (2012) utilized a dynamic objective function and a predictive model of the public transport system to make decisions on holding and stop-skipping. The uncertain passenger demand was included in the model as a disturbance, and the resulting NP-hard problem was solved using an ad hoc implementation of a genetic algorithm. Luo et al. (2017) proposed a nonlinear optimization model to improve the headway adherence considering vehicle capacity. In Luo et al. (2017), the vehicle capacity was not explicitly modeled as a problem constraint. Instead, they aimed at maintaining a stable passenger load within the vehicles. Li et al. (2019) also considered the demand uncertainty that can affect the vehicle loads when applying holding. However, the vehicle capacity was not explicitly considered in their problem formulation. The same holds true in the target-headway-based holding approach of He et al. (2020). In He et al. (2020), the capacity limit is not explicitly considered in the problem formulation but it is used to stop loading passengers until unoccupied space is available at a later stop. Finally, Koehler et al. (2018) proposed an integrated holding and priority control model for bus rapid transit services. Koehler et al. (2018) considered vehicle capacity in the model formulation. This resulted in a mixed integer nonlinear program that cannot be solved effectively in large scale problem instances and does not guarantee the computation of globally optimal solutions.

The aforementioned works are the main ones that incorporate capacity limitations in the holding optimization process. Nevertheless, except the recent work of Gkiotsalitis and van Berkum (2020a) that considers the impact of holding a vehicle to its following trip, they do not offer an analytic solution. In more detail, due to their complexity and their non-convex nature, the proposed multi-variable mathematical programs cannot be solved to global optimality in real-time. To summarize the holding literature, Table 1 presents a summary of selected holding works and analyzes their characteristics in terms of the number of decision variables, objective

Table 1
Summary of selected holding methods.

Study	Decision Variables	Objective function	Mathematical Program	Stochasticity	Solution Method	Capacity
Sánchez-Martínez et al. (2016)	multivariable	waiting time and in-vehicle delay	non-convex	ignored	Algorithm of Powell (2009)	considered
Delgado et al. (2012)	multivariable	waiting time, in-vehicle delay and extra waiting time of stranded passengers	non-convex	ignored	MINOS solver	considered
Hickman (2001)	single variable	waiting time and in-vehicle delay	convex	considered	line search	ignored
Eberlein et al. (2001)	multivariable	waiting time	non-convex	ignored	purpose-built heuristic	ignored
Sun and Hickman (2008)	multivariable	waiting time and in-vehicle delay	convex	ignored	decomposition-based heuristic	ignored
Zolfaghari et al. (2004)	multivariable	waiting time and extra waiting time of stranded passengers	convex	ignored	simulated annealing	considered
Puong and Wilson (2008)	multivariable	waiting time, in-vehicle delay and extra waiting time of stranded passengers	non-convex	ignored	decomposition-based heuristic	considered
Zhao et al. (2003)	single variable	waiting time and in-vehicle delay	non-convex	considered	multiagent negotiation heuristic of Sandholm (1993)	ignored
Wu et al. (2017)	single variable	waiting time	non-convex	ignored	first-depart-first-hold rule	considered
Bartholdi and Eisenstein (2012)	single variable	equalize headways	no program	ignored	closed-form expression	ignored
Berrebi et al. (2015)	multivariable	waiting time	no program	considered	dynamic programming	ignored
Fu and Yang (2002)	single variable	waiting time	no program	ignored	closed-form expression	ignored
Gkiotsalitis and Cats (2019)	multivariable	waiting time and in-vehicle delay	non-convex	ignored	branch and bound	ignored
Sáez et al. (2012)	multivariable	waiting time, in-vehicle delay and extra waiting time of stranded passengers	non-convex	considered	genetic algorithm	considered
Xuan et al. (2011)	single variable	guaranteeing a maximum standard deviation from the schedule	non-convex	considered	closed-form expression	ignored
Hernández et al. (2015)	multivariable	waiting time, in-vehicle delay and extra waiting time of stranded passengers	non-convex	ignored	MINOS solver	considered

function, mathematical program properties, stochasticity, solution method, and consideration of vehicle capacity. As can be seen, several studies have solely considered passengers waiting times, neither considering the impacts of holding times for passengers held on-board nor the potentially prolonged vehicle trip times. Since waiting times are bound to improve with a more regular service, an analysis that does not consider the downsides of slowing down a service is incomplete and may provide a biased assessment.

In terms of implementation, more detailed holding models that consider vehicle capacity are typically non-convex and hard-to-solve in near real-time, thus hampering their practical applicability. On the other hand, easy-to-solve models that provide analytic solutions typically consider the impact of holding on a preceding and a following vehicle resulting in myopic solutions that fail to investigate the potential side-effects to the rest of the vehicles operating in the line.

4. Rescheduling

The rescheduling of services focuses on the modifications of the dispatching times of future trips. Unlike holding, rescheduling is allowed to modify the departure time of a trip at a single stop (the first stop). That is, rescheduling can be viewed as a special case of holding where the decision is made at the first stop only. Potential stop-skipping and/or holding actions can be easily applied on top of rescheduling as soon as the vehicles are en-route (Zhao et al., 2003; Cats et al., 2011).

Before concentrating on public transport rescheduling in urban settings, we briefly note dynamic rescheduling works in train operations. Rescheduling solutions in train operations commonly adopt local re-timing to adjust the timetable (see D'Ariano et al. (2008, 2010, 2014, 2020)). D'Ariano et al. (2008) aimed to improve the punctuality of trains by routing and sequencing trains in an iterative manner. This work was extended in Corman et al. (2010) by incorporating effective rescheduling algorithms and local rerouting strategies in a Tabu search scheme. Corman et al. (2010) alternated between a fast heuristic and a truncated B&B algorithm for computing train schedules within a short computation time without guaranteeing the convergence to a globally optimal solution. Pellegrini et al. (2014) aimed to minimize delays after an unexpected disturbance disrupts operations by seeking the best train routing and scheduling. Krasemann (2012) introduced a greedy heuristic to ensure that a (hopefully) good-enough rescheduling solution is obtained within a short time (within 30 s). To this end, Krasemann (2012) provided a heuristic solution method without modelling the timetable rescheduling problem as a mathematical program.

Most works on rescheduling model the problem as an integer mathematical program where the decision variables are the dispatching times of trips. That is, the originally planned dispatching times of trips are allowed to be modified when applying rescheduling. Due to their discrete nature, rescheduling problems cannot be easily solved and many timetabling approaches try to avoid the need for rescheduling by producing robust timetables that can perform well under travel time and passenger demand disruptions (Tang et al., 2019; Gkiotsalitis and Alesiani, 2019). Several works have employed rescheduling to adjust the dispatch times of trips to the travel time and passenger demand variations. Bly (1976) used rescheduling of depleted services to provide equal headways for the available fleet in the schedule. Gkiotsalitis and Stathopoulos (2016) proposed a rescheduling strategy that modifies the dispatching times of vehicle trips to match the passenger demand of individuals who want to participate in joint activities using a genetic algorithm. Gkiotsalitis (2019a) proposed periodic rescheduling that does not focus only on the running buses, but reschedules the dispatching times of all remaining daily trips while considering operational constraints related to layover times and capacity limits. Li et al. (2008) modeled and solved the single depot rescheduling problem in pseudo-polynomial time using a parallel auction algorithm. In a follow-up work, Li et al. (2009) showed that the rescheduling problem is NP-hard, and used a Lagrangian relaxation-based insertion heuristic for its solution.

In Gkiotsalitis and van Berkum (2020b), the rescheduling problem was modeled as a convex continuous optimization problem where trips were periodically rescheduled in rolling horizons. Gkiotsalitis and van Berkum (2020b) proved that the rescheduling problem is not convex when the vehicle capacity is considered in the optimization process. If, however, the vehicle capacity is not

Table 2
Summary of selected rescheduling works.

Study	Problem	Mathematical Program	Stochasticity	Solution Method
Gkiotsalitis and Stathopoulos (2016)	rescheduling	integer nonlinear	no	genetic algorithm
Li et al. (2008)	rescheduling	integer linear	no	parallel action algorithm
Li et al. (2009)	rescheduling	integer linear	no	Lagrangian relaxation-based heuristic
Mirchandani et al. (2010)	rescheduling and signal priority	macroscopic model	no	heuristic
Gkiotsalitis (2019a)	rescheduling	integer nonlinear	no	sequential hill climbing
Cevallos and Zhao (2006a)	rescheduling considering passenger transfers	integer program	no	genetic algorithm
Coffey et al. (2012)	rescheduling considering passenger transfers	linear program	no	CPLEX
Gkiotsalitis and van Berkum (2020b)	rescheduling	nonlinear convex program	no	CPLEX
Rizopoulos and Saharidis (2020)	rescheduling considering passenger transfers	mixed-integer linear program	no	CPLEX
Gkiotsalitis (2020b)	rescheduling	quadratic convex program	no	analytic solution
Altazin et al. (2017)	rescheduling and stop-skipping	integer nonlinear program	no	CPLEX

considered, the rescheduling problem can be solved to global optimality. This approach was later extended in Gkiotsalitis (2020b), where an analytic solution for the rescheduling problem in rolling horizons was introduced. The analytic solution returned an updated schedule significantly faster than exact optimization approaches for quadratic programming and maintained a negligible optimality gap in realistic operation scenarios.

Given that rescheduling alone results in marginal improvements, several works have coupled rescheduling with additional control measures. Mirchandani et al. (2010) coupled rescheduling with signal priority to improve the service regularity after a disruption. Altazin et al. (2017) proposed a combination of rescheduling and stop-skipping in which stops can be skipped and services can be retimed.

Finally, we should note that rescheduling is used for synchronization among services to reduce the transfer waiting times of passengers. Cevallos and Zhao (2006a) and Cevallos and Zhao (2006b) proposed simple perturbations by merely shifting the pre-existing timetables to solve the aforementioned problem and resorted in a genetic algorithm given the computational complexity of the problem. In addition, Coffey et al. (2012) treated the synchronization problem as a demand–supply matching problem. In their approach, they rescheduled the timetables of public transport modes by matching passenger demand expressed via journey planners with the public transport supply to reduce missed connections. Rizopoulos and Saharidis (2020) developed mixed integer-linear programming models to achieve service synchronization among different lines via rescheduling. A summary of selected rescheduling methods discussed in this section is provided in Table 2.

To summarize, one first observation is that the rescheduling literature is fairly limited compared to the literature on vehicle holding. Importantly, rescheduling is typically coupled with other control measures, such as holding, and it is applied as a standalone measure in limited cases. This can be justified because rescheduling only impacts the dispatching times of trips and cannot mitigate potential irregularities appearing at intermediate stops. This is also a reason why rescheduling is mostly applied for synchronizing services provided by different lines and it has limited applicability for improving the regularity of a single line.

In terms of practical implementation, rescheduling models that consider the synchronization of lines are hard-to-solve and past literature typical resorts to heuristics. Because of this, it is not always guaranteed that an efficient solution can be computed in near real-time. The same applies for models that couple rescheduling with vehicle holding. Standalone rescheduling models that only consider the regularity of services have the most preferable model formulations that allow to return a globally optimal solution in real-time. However, as previously mentioned, standalone rescheduling might have a limited effect on improving the service regularity if it is not coupled with other control measures.

5. Stop-skipping

Stop-skipping (also known as expressing) is a control measure that allows a vehicle to skip a stop (or a series of stops) if it is running behind schedule. Stop-skipping can correct service inconsistencies due to the inherent travel time and passenger demand variations, but might result in increased waiting times for passengers waiting at the skipped stops (Chen et al., 2015c). Thus, most stop-skipping approaches address the problem holistically considering the waiting times of passengers, their in-vehicle times, and the total vehicle trip travel times. The two former objectives concern the passenger-related costs, whereas the last objective concerns the cost of the operator.

Addressing the stop-skipping problem at the operational level requires computing a stop-skipping solution in near real-time. Given the computational complexity of the stop-skipping problem, a line of research considers the stop-skipping strategy of only one trip at a time to reduce the size of the solution space (Fu et al., 2003; Liu et al., 2013). Such treatment enables the computation of a stop-skipping solution for typical services with fewer than 20 stops, but results in myopic control options because it addresses every trip in isolation without acknowledging that it belongs to a chain of trips (Bartholdi and Eisenstein, 2012).

Inherently, stop-skipping is a binary, 0–1 optimization problem where a stop can be skipped (0) or served (1). If we consider the single trip that operates in the service line of Fig. 2 and can skip/serve every stop, the solution space of potential skip/serve options is $2^{|S|}$, where $|S|$ is the total number of stops. This exponential increase of the solution space with the number of stops allows evaluating all solution space options with the use of brute-force for lines that typically do not exceed 20 stop-skipping candidate stops (Fu et al., 2003).

Other approaches calculate a stop-skipping plan for the entirety of daily trips or for several trips in a rolling horizon (Jordan and

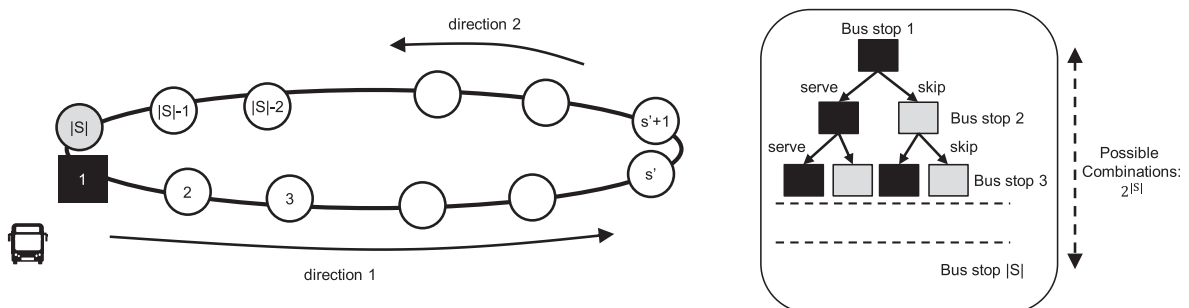


Fig. 2. Service operating in a loop with $s = \{1, 2, \dots, |S|\}$ stops that can be either skipped or served.

Turnquist, 1979). Nevertheless, such approaches cannot be applied in real-time control because of the exponential increase in computational costs when considering more than one trip. In more detail, if we consider multiple trips, $|N|$, and multiple stop-skipping candidates, $|S|$, devising an optimal stop-skipping plan requires evaluating all the solutions from the solution space $2^{|N||S|}$ which grows exponentially with the number of trips and stops.

Stop-skipping strategies can be devised at either the tactical planning level or the operational level (dynamic stop skipping). Depending on the level of control, the objectives of a stop-skipping strategy might differ. At the tactical planning stage, the focus is on developing reliable, resilient or robust strategies that will maintain a good performance in case of disruptions during actual operations. Stop-skipping can be addressed at the tactical planning stage where a stop-skipping plan is devised before the start of the daily operations and is not updated afterwards (Jordan and Turnquist, 1979; Furth, 1986). The advantage of a fixed stop-skipping plan is that it can be communicated to the drivers and passengers well in advance. However, a fixed stop-skipping plan is inflexible and cannot be modified during actual operations. Furth and Day (1985) and Furth (1986) analyzed the effect of four pre-planned strategies (short-turning, restricted zonal service, semi-restricted zonal service, and stop-skipping) to service lines with unbalanced demand between directions. The explored objectives were the minimization of the fleet size and the improvement of the passenger-related cost. Gkiotsalitis (2019b) proposed a combination of genetic algorithm and linear programming to develop a stop-skipping strategy for the entire day of operations which performs well for worst-case scenarios (robust stop-skipping plan). The approach was tested in a circular bus line in Singapore demonstrating a potential performance improvement of more than 10% for worst-case scenarios. Jamili and Aghaee (2015) focused on finding optimal stop-skipping patterns in railway systems. They developed robust stop-skipping plans using a decomposition-based algorithm and a simulated annealing-based algorithm. Wu et al. (2019) proposed a robust optimization model for the stop-skipping problem considering vehicle overtakings and demand dynamics for minimizing the user and operation costs at the tactical planning phase. Finally, Chen et al. (2015b) considered the vehicle capacity and stochastic travel times while solving the offline stop-skipping problem with an artificial bee colony heuristic.

In contrast to stop-skipping at the tactical planning level, dynamic stop-skipping strategies at the operational level are reactionary and less sophisticated because they need to be computationally efficient. In dynamic stop skipping, the skipped stops of a vehicle trip are determined just before dispatch (Li et al., 1991; Lin et al., 1995; Eberlein, 1997; Fu et al., 2003). If one focuses on the stop-skipping decisions of a single vehicle, the solution space comprises $2^{|S|}$ different options where $|S|$ is the total number of stops that can be optionally skipped. Despite the exponential increase of the solution space, it is possible to explore the solution space of all available stop-skipping options in medium-sized service lines with up to 20 stops (Fu et al., 2003; Sun and Hickman, 2005).

Sun and Hickman (2005) solved the stop-skipping problem using an exhaustive search after modelling it as a nonlinear integer program and considering random distributions of passenger boardings and alightings. Similarly, Fu et al. (2003) determined the skipped stops of one vehicle at a time using an exhaustive search. Fu et al. (2003) considered the passenger-related waiting times and the trip travel times in a stop-skipping simulation of route 7D in Waterloo, Canada. In that work, two consecutive vehicle trips were not allowed to skip the same stop. Liu et al. (2013) proposed a stop-skipping model for individual vehicles which did not allow their preceding and following vehicles to skip any stops. Liu et al. (2013) used a genetic algorithm incorporating Monte Carlo simulations for the solution of their mixed-integer, nonlinear program.

Eberlein (1995) developed a simplified transit operation environment where the stop-skipping problem was modeled as an integer nonlinear program with quadratic objective function and constraints. In a later work, Eberlein et al. (1998) modeled the stop-skipping problem as an integer nonlinear program considering the passenger waiting times as an objective function and solving the stop-skipping problem in rolling horizons. In each rolling horizon, the skipped stops of all trips $i \in I_m$, where I_m is the set of all trips that belong to the rolling horizon, were determined. Given the complexity of the integer non-linear program, Eberlein et al. (1998) simplified the model formulation and proposed an analytic solution that can be applied to the simplified problem. This approach was tested on the Green Line of the Massachusetts Bay Transportation Authority. Gkiotsalitis (2020) introduced a rolling horizon stop-skipping model to determine the stop-skipping strategies of several trips within a rolling horizon. The model was an integer nonlinear program and it was solved to global optimality for small-scale scenarios.

Stop-skipping has also been combined with short-turning allowing vehicles to operate smaller parts of the line. In Li et al. (1991), the stop-skipping and short-turning problems were combined and were formulated as a 0–1 stochastic programming problem. Their formulation considered operational disruptions and the accommodation of passenger demand. Because of the problem complexity, Li et al. (1991) used heuristics and tested the solution performance with sample data from the Shanghai Transit Company.

Stop-skipping has also been combined with holding (Eberlein, 1995; Lin et al., 1995; Cortés et al., 2010; Sáez et al., 2012) and vehicle scheduling (Cao and Ceder, 2019). Cortés et al. (2010) applied control decisions when vehicles arrived at stops by solving the combined stop-skipping and holding problem with a genetic algorithm-based multi-objective optimization approach. Lin et al. (1995) also combined stop-skipping with holding and measured the system performance in terms of passenger in-vehicle time and waiting time. Similarly, Sáez et al. (2012) considered uncertain passenger demand and formulated the combined problem as a hybrid predictive control problem. We finally note that stop-skipping has also been used in metro and rail operations for recovering after disruptions (Gao et al., 2016; Cao et al., 2016; Altazin et al., 2017).

Typical objectives of the stop-skipping problem are the following:

- O1: waiting time of passengers;
- O2: in-vehicle time of passengers;
- O3: vehicle travel time;
- O4: reduction of control actions;

- O5: deviation from the planned schedule;
- O6: unsatisfied demand;
- O7: inconvenience of passengers that need to alight when skipping their stop.

To summarize the stop-skipping literature, in Table 3 we present a summary of stop-skipping works and analyze their characteristics in terms of problem attributes, number of decision variables, optimization horizon, objective function, mathematical program properties, stochasticity, and solution method. Unlike vehicle holding and rescheduling methods that have more standardized objectives, stop-skipping works consider various key performance indicators that address both the operational-related costs and the passenger-related costs. The major problem with stop-skipping approaches is their practical applicability. The stop-skipping problem is a hard-to-solve 0–1 problem that can only be solved in near real-time if the number of decisions are very limited (e.g., only if we decide about the skipped stops of one vehicle at a time and the service line operates a limited number of stops). This main issue offers a clear challenge for future researchers in this field to devise intelligent solution algorithms to mitigate the computational costs and solve stop-skipping problems in larger instances.

It is also worth noting that, unlike rescheduling and holding, stop-skipping impacts the composition of the service line since many stops might not be served. That is, a number of origin–destination pairs might not be accommodated when applying stop-skipping. This has major implications for the service of passenger demand and stop-skipping works should study this issue in more detail. Potential issues worthy of investigation are the locations of stops that can be skipped to ensure that stops with significant passenger demand are not skipped. The stops that can be skipped should also differ from vehicle to ensure that a stop cannot be skipped by consecutive vehicles leading to excessive waiting times.

6. Key trends and challenges: towards a research agenda

Notwithstanding the large body of research devoted to at-stop control measures, emerging trends in public transport planning and operations pose new research challenges. While some of the classic control problems (e.g., single-line rescheduling or headway-based holding control) have been exhausted and can be considered largely solved, recent modeling and technological advancements pave the way for a new research agenda. In the following, we elaborate on five research directions that we have identified as the most pressing and promising ones. These research challenges either directly respond to the limitations discussed above or in response to external changes in the operational environment. The first three directions challenge the research community to shift from single measure, supply-based and single line control strategies to an integrated passenger-focused network-wide control scheme. The two additional directions respond to the on-going electrification of public transport fleets and the increasing focus on disturbance management. Rapid developments in data collection, processing and related analysis and prediction techniques serve as enablers for many of these research directions.

6.1. Beyond a single measure

As is evident from the review provided in the previous sections, at-stop control measures - holding control, rescheduling and stop

Table 3
Summary of selected stop-skipping works.

Study	Problem	Trips considered	Real-time	Objective function	Mathematical Program	Stochasticity	Solution Method
Fu et al. (2003)	stop-skipping	one	yes	O1 + O2 + O3	integer nonlinear	no	brute-force
Cortés et al. (2010)	stop-skipping and holding	multiple	yes	O1 + O4	mixed-integer nonlinear	no	genetic algorithm
Gkiotsalitis (2019b)	stop-skipping	multiple	no	O1 + O2 + O3	integer linear	yes	genetic algorithm
Liu et al. (2013)	stop-skipping	one	yes	O1 + O2 + O3	integer non-linear	yes	genetic algorithm
Li et al. (1991)	stop-skipping and short-turning	one	yes	O5 + O6	integer nonlinear	yes	heuristic
Lin et al. (1995)	stop-skipping and holding	one	yes	O1 + O2 + O3 + O5	mixed-integer	no	–
Eberlein et al. (1998)	stop-skipping	multiple	yes	O1	integer non-linear	no	analytic solution for a simplified model
Sáez et al. (2012)	stop-skipping and holding	multiple	yes	O1 + O2	mixed integer non-linear	yes	genetic algorithm
Sun and Hickman (2005)	stop-skipping	one	yes	O1 + O7	integer non-linear	no	brute-force
Jamili and Aghaee (2015)	stop-skipping	multiple	no	O3	integer non-linear	yes	decomposition and simulated annealing
Chen et al. (2015b)	stop-skipping	multiple	no	O1 + O2 + O3	integer non-linear	yes	artificial bee colony
Wu et al. (2019)	stop-skipping	multiple	no	O1 + O3	integer non-linear	yes	response surface methodology
Gkiotsalitis (2020)	stop-skipping	multiple	yes	O1 + O2 + O3	integer non-linear	no	brute-force and heuristics

skipping - have been predominantly applied in isolation. There is however increasing evidence to suggest that combining control measures can yield service improvements. Sáez et al. (2012) combine holding control with stop skipping using a meta-heuristic as a solution approach. Delgado et al. (2012) analyze service performance when complementing holding control with a limited boarding policy. The latter implies limiting the number of passengers permitted to board the vehicle in order to improve service operations. While such a measure may be beneficial for service performance, its acceptance by service users and service providers requires further investigation. The range of possible measures was further extended by Nesheli and Ceder (2017) who combined holding, boarding limits, stop skipping at stops as well as speed adjustments between stops. Their objective function minimizes total passenger travel time and maximizes the number of direct transfers. Leffler et al. (2017) formulate a real-time short-turning control decision for a bi-directional service introduced on top of holding control. These works demonstrate the potential of combining control measures to achieve overall service improvements. Wood et al. (2018) also proposed a decision rule to determine whether to hold or skip stops based on the impacts on passenger net travel savings. Looking forward, future developments may consider a greater diversity of control measures by also considering between-stops measures including signal priority and speed adjustments in addition to various at-stop measures.

6.2. Towards passenger-oriented decision making

The operations and control of public transport systems have been traditionally dominated by supply-side considerations and this has been reflected in vehicle-based performance metrics. Control measures were therefore focused on either vehicle punctuality, the extent to which the scheduled departure times were met, or on vehicle regularity, the variation in service headway. Such vehicle-based metrics are sometimes used as an approximation of passenger impacts. The state-of-the-art has now shifted more towards passenger-oriented decision making by leveraging on the increasing availability of passenger-related data.

Recent studies often apply passenger loads as weights to vehicle-based metrics, i.e. headway and trip time may be used to approximate passengers waiting times and passenger (perceived) in-vehicle time. Most works incorporate different travel time components into a single-objective function that combines multiple objectives with the use of weight factors. However, the terms may not be fully compensatory due to the requirement of either guaranteeing certain service standards or satisfying certain user groups. There is therefore a need for future research to employ multi-objective approaches that derive Pareto frontiers. Furthermore, there is lack of behavioral knowledge on users' acceptance of alternative control strategies and their associated adversities (e.g. waiting at a skipped stop, being held on-board a vehicle).

While applying passenger-related factors as weights can provide some indication of passenger-related effects, there are two major limitations: (i) a whole journey passenger perspective extends beyond the single line and requires the consideration of the transfer experience; (ii) passengers may make different travel choices in the presence of control measures. For instance, they may decide to board another service if their stop has been skipped. The latter is especially relevant in dense and saturated networks where passengers have many routing alternatives and crowding might affect their choices, calling for the consideration of vehicle capacity limits and creating greater inter-dependency between travellers' choices. Passenger re-distribution effects have therefore been recently introduced into tactical planning decisions such as timetable planning and frequency determination (Parbo et al., 2014; Cats and Glück, 2019). In the context of real-time control, the inclusion of passenger re-distribution effects requires the use of a dynamic transit assignment model to evaluate the downstream consequences of alternative measures. This is expected to increase the complexity of real-time control models significantly, thus increasing the need for efficient solution methods.

As is true for any control measure, performance depends on the quality of the underlying predictions. Passenger-oriented control decisions ultimately demand reliance on the real-time predictions of traffic conditions and passenger flows. This is needed to assess the number of passengers waiting, travelling on-board, transferring and denied boarding, and the respective passenger time losses or gains caused by a certain intervention (see Gavriilidou and Cats (2018)). Such predictions can be based on historical data or real-time measurements of vehicle locations (Moreira-Matias and Cats, 2016), passenger counts or fare collection data, with real-time sources being superior in supporting control decisions (Gavriilidou and Cats (2018)). Moreover, uncertainty analysis may be performed to assess the risk associated with the stochasticity associated with the predicted values (e.g. travel times, passenger load) to improve the robustness of the control decisions made.

The increasing availability of large and diverse data sources enables the development of new travel time and passenger flow prediction schemes. Predictions concerning these two components are essential as the optimization and assessment of various control strategies relies on the numbers of passengers affected and the magnitude of the effect. Crowd-sourcing, social media, on-board counting techniques (e.g. cameras, door counts), and automated fare collection (AFC) - in particular in the form of smart card data validation, all offer promising opportunities for developing more accurate and reliable flow predictions. Given this emergence of Big data, short-term prediction techniques often involve the application of machine learning techniques (e.g. (Ma et al., 2014; Moreira-Matias et al., 2016; Li et al., 2017; Toqué et al., 2017)). Such developments can support the implementation of more informed control decisions.

At this point, we should also note that machine learning methods can also be used for proposing control measures. Although research in this direction is at its early stages, reinforcement learning approaches have emerged as alternatives to traditional mathematical optimization models when making control decisions. In more detail, Alesiani and Gkiotsalitis (2018) and Wang and Sun (2020) used reinforcement learning to determine the holding times of multiple trips instead of solving a mathematical program. By using reinforcement learning, the running vehicles are modeled as agents and a headway-oriented reward function is defined to explore the effects of potential holding strategies. Chen et al. (2015a) also proposed a multi-agent reinforcement learning approach for holding control strategies. Apart from vehicle holding, Jiang et al. (2018) and Saw et al. (2019) also recently studied the application of

reinforcement learning for devising no-boarding or passenger control strategies. Finally, reinforcement learning has also been used for train rescheduling in a number of recent studies (e.g., Šemrov et al. (2016, 2018,)). Reinforcement learning has the disadvantage of requiring an initial training period where the proposed control measures are of low accuracy and might be counterproductive. Once this training period is over though, reinforcement learning can provide immediate control suggestions without the need of solving complicated, time-consuming mathematical optimization problems.

6.3. Beyond a single-line, towards network-level

The vast majority of studies devoted to transit operations investigate control strategies at the individual line-level. Even if the strategy is applied and evaluated at the network-level, it is designed for each line in isolation where the operation of each line is controlled independently. However, single-line control which disregards other lines in its decision-making may hamper performance at the network-level. Coordinated network control is expected to be especially important when there are significant interactions between lines. We can distinguish between two types of inter-line interactions: (i) a considerable share of passengers' journeys involves transferring from one line to another; (ii) the network includes common corridors where several lines run in parallel and a considerable share of the passengers travel within the same corridor.

Transfer synchronization can be embedded into holding rules by taking into account the vehicles originating from lines other than the controlled one and regulating departure times so as to minimize transfer times. Dessouky et al. (2003) introduced transfer time as a component of the total time that the holding rule is designed to minimize. Hadas and Ceder (2010) defined direct transfers as the simultaneous arrival of vehicles from two lines and applied holding control so as to maximize the number of direct transfers. This work was extended by Nesheli et al. (2015) who considered a combination of strategies using a mathematical programming model. A controller which optimally sets holding times with the goal of reconciling single-line regularity objectives with multi-line transfer synchronization was proposed by Gavriilidou and Cats (2019). Their formulation involves the minimization of the generalized travel cost while considering different passenger prediction schemes depending on the availability of passenger-related information in real-time. All of the aforementioned studies have considered a single interchange stop between two transit lines. There is thus a lack of knowledge on how to scale such control measures up to more complex network configurations and the potential benefits they may yield.

A new line of research addresses a common network configuration, namely transit corridors. While the aforementioned studies have considered transfer synchronization in the event that lines intersect at a single interchange location, the geometry of public transport networks is often such that there is a sequence of stops along a shared corridor where a transfer can be made. This is the outcome of public transport networks typically consisting of trunks aimed at serving a high-demand corridor with lines before and/or after the trunk branch out to serve areas with lower demand. Managing such network configurations requires making compromises between the service regularity of individual lines, the service regularity of the joint line operations along the trunk as well as transfer synchronization at interchange stations. Recent advancements include network-wide scheduling which considers service regularity and transfer synchronization at the tactical level, as proposed in Gkiotsalitis et al. (2019a). Several recent efforts have investigated real-time control measures for corridor management. Hernández et al. (2015) compared the performance of a joint control versus single-line control, limited to the joint section. Similarly, Fabian and Sánchez-Martínez (2017) performed a simulation-based comparison of schedule-based and headway-based holding control for a multi-branch urban rail network. Argote-Cabanero et al. (2015) extended the work of Xuan et al. (2011) from single-line holding control to multi-line control. Seman et al. (2019) formulated an optimization holding control problem which aimed to minimize the waiting times of passengers originating at stops located along the shared corridor while accounting for denied boarding due to capacity constraints. Laskaris et al. (2019) explicitly expressed the trade-offs between different objectives corresponding to distinct passenger groups when lines merge from branches into a common trunk. They showed that coordinating vehicle arrivals from the merging lines as well as the regularity of each line by holding vehicles upstream of the merging stop can yield consistent network-wide travel time savings.

6.4. Going electric

The rapid deployment of electric buses introduces a new set of operational considerations and requirements that may affect control measures. Past works on electric buses focused overwhelmingly on their ramifications for strategic and tactical planning. This includes the charging station location problem generation (Wang et al., 2017) and scheduling of feasible electric bus routes (Tzeng et al., 2005; Miles and Potter, 2014), and the daily vehicle scheduling problem considering vehicles' availability, passengers' waiting times and charging times and costs (Zheng et al., 2014; Li, 2014; Wen et al., 2016; Teng et al., 2020).

The aforementioned studies are limited to the strategic and tactical planning aspects that emerged from the introduction of electric buses. Battery charging requirements may impose, however, hard or soft constraints on real-time control measures. Hard constraints refer to a vehicle's ability to complete its trips while soft constraints pertain to energy consumption and power grid utilization (see Gkiotsalitis (2020a)). For example, at-stop charging stations may require distributing holding times differently across stops. Such considerations may be combined with eco-driving and transit signal priority schemes aimed at minimizing energy consumption between stops. Moreover, the capacity of charging facilities may become restrictive in the event of discrepancies between planning and operations for electric buses resulting in a number of electric buses being in need of a limited number of charging stations at the same time (Zheng et al., 2014). This may induce delays to bus services as well as put pressure on the power grid (Srinivasaraghavan and Khaligh, 2011; Foster et al., 2013; Clement-Nyns et al., 2010; Richardson, 2013). There is thus a clear need for the development of control measures that account for the unique features of electric fleets.

6.5. Disturbance management

Real-time control measures have been designed primarily to cope with small fluctuations caused by the underlying variability of passenger demand, traffic conditions, driver behavior and operations. Such measures may not perform well in the event of major disturbances that require the deployment of timetable recovery techniques to cope with poor rolling stock circulation. In fact, some of the control measures devised for addressing small fluctuations may even become counterproductive or insensible when encountering a major disturbance. For example, in the case that a vehicle is dispatched to maintain an even headway but arrives late at the terminal, delays the dispatching of that vehicle's subsequent trip. To this end, [Gkiotsalitis et al. \(2020\)](#) formulate and solve the real-time control problem of optimally dispatching metro services following a major disturbance.

In the context of railway systems, there are ample algorithms for managing disruptions given the highly constrained operational environment involving the rescheduling and short-turning of services (for a discussion see [Ghaemi et al. \(2017\)](#)). Another body of research has been devoted to the optimal deployment of bus bridging services in the event of severe rail disruptions resulting in the closure of tracks and stations ([Kepaptsoglou and Karlaftis, 2009b](#)). There is, however, a lack of research on how at-stop measures can contribute to mitigating the impact of recurrent service disturbances. For example, stop skipping can be applied in response to station capacity reduction. Notwithstanding this, there is a lack of mathematical models for stop-skipping control in rolling horizons with most works determining the skipped stops of each trip when it is about to be dispatched. With the increasing focus in transport on system robustness, it is expected that service providers will devote more attention in the coming years to real-time disturbance management schemes given their potential to reduce passenger delays under adverse circumstances.

7. Conclusion

In this paper we reviewed and synthesized the state-of-the-art on public transport at-stop control measures that can be applied in real time. This family of measures consists of holding, dynamic dispatching, and stop skipping. In reviewing related work, we focused on the formulation of the proposed mathematical models, the resulting computational complexity, and its consequences for real-time deployment. We categorized and compared past works in relation to the selection of decision (control) variables, the formulation of objective functions, the properties of the mathematical programs, and the respective solution methods employed.

Our first observation is that standalone rescheduling works have a relatively limited impact on improving the service regularity. Because of this, more research is needed in the direction of combining rescheduling with other at-stop control measures, such as vehicle holding and stop-skipping. Concerning vehicle holding, most studies propose holding measures to improve service regularity. However, the potential downside of slowing down the service is rarely considered. In addition, easy-to-solve models that provide analytic vehicle holding solutions typically consider the impact of holding a vehicle on its neighboring vehicles resulting in myopic solutions. Finally, stop-skipping studies can study further the major implications of skipping a stop to unserved passengers. Potential issues worthy of investigation are the locations of skipped stops to ensure that we always serve stops with significant passenger demand and the frequency of skipping a stop to ensure that a stop is not skipped repeatedly.

We also identified five themes in setting a research agenda pertaining to the combination of control measures, passenger-oriented decision making, coordinated network control, deployment of electric buses and disturbance management. Developments in these themes require state estimation as well as the analysis of the dynamics of traffic and passenger flows. As demonstrated by this review, the performance and complexity of control measures has advanced significantly in recent years. Notwithstanding this, research into control measures has clearly not yet been exhausted and new challenges for service operations and new opportunities in terms of real-time data provision and improved computational capabilities offer new avenues for advancing the real-time control of public transport systems. Finally, empirical evidence from field implementation is still relatively limited, in particular for control strategies other than holding.

Appendix A. Basic optimization terminology

- **continuous convex program:** it is a mathematical program with convex objective function and convex feasible set. In continuous optimization, a convex program can be typically solved to global optimality with conventional exact optimization solvers because every locally optimal solution derived by a solver is also a globally optimal one;
- **continuous non-convex program:** it is a mathematical program that has a non-convex objective function or non-convex feasible set. Such program may have multiple feasible regions and multiple locally optimal points within each region; thus, it is not always possible to guarantee the convergence to a globally optimal solution;
- **discrete (or integer) program:** it is a mathematical program with discrete decision variables (very common in rescheduling and stop-skipping problems). Solving such programs to global optimality might require the exploration of the entire solution space;
- **mixed-integer program:** it is a mathematical program which has both discrete and continuous decision variables (i.e., a mixed-integer formulation can be used for the combined stop-skipping and holding problem);
- **heuristic:** a solution method that returns a solution to a mathematical program by exploring only a fraction of the solution space without guaranteeing global optimality.

References

- Abkowitz, M., Tozzi, J., 1987. Research contributions to managing transit service reliability. *J. Adv. Transport.* 21 (1), 47–65.
- Adamski, A., Turnau, A., 1998. Simulation support tool for real-time dispatching control in public transport. *Transport. Res. Part A: Policy Pract.* 32 (2), 73–87.
- Alesiani, F., Gkiotsalitis, K., 2018. Reinforcement learning-based bus holding for high-frequency services. In: 2018 21st International Conference on Intelligent Transportation Systems (ITSC). IEEE, pp. 3162–3168.
- Altazin, E., Dautzère-Pérés, S., Ramond, F., Tréfond, S., 2017. Rescheduling through stop-skipping in dense railway systems. *Transport. Res. Part C: Emerg. Technol.* 79, 73–84.
- Ampountolas, K., Krings, M., 2015. Mitigating bunching with bus-following models and bus-to-bus cooperation. In: 2015 IEEE 18th International Conference on Intelligent Transportation Systems. IEEE, pp. 60–65.
- Ampountolas, K., Krings, M., 2020. Mitigating bunching with bus-following models and bus-to-bus cooperation. *IEEE Trans. Intell. Transp. Syst.*
- Argote-Cabanero, J., Daganzo, C.F., Lynn, J.W., 2015. Dynamic control of complex transit systems. *Transport. Res. Part B: Methodol.* 81, 146–160.
- Bartholdi, J.J., Eisenstein, D.D., 2012. A self-coordinating bus route to resist bus bunching. *Transport. Res. Part B: Methodol.* 46 (4), 481–491.
- Bellei, G., Gkoumas, K., 2009. Threshold-and information-based holding at multiple stops. *IET Intel. Transport Syst.* 3 (3), 304–313.
- Berrebi, S.J., Crudden, S.O., Watkins, K.E., 2018a. Translating research to practice: Implementing real-time control on high-frequency transit routes. *Transport. Res. Part A: Policy Pract.* 111, 213–226.
- Berrebi, S.J., Hans, E., Chiabaut, N., Laval, J.A., Leclercq, L., Watkins, K.E., 2018b. Comparing bus holding methods with and without real-time predictions. *Transport. Res. Part C: Emerg. Technol.* 87, 197–211.
- Berrebi, S.J., Watkins, K.E., Laval, J.A., 2015. A real-time bus dispatching policy to minimize passenger wait on a high frequency route. *Transport. Res. Part B: Methodol.* 81, 377–389.
- Bly, P., 1976. Depleted bus services: the effect of rescheduling. *Tech. rep.*
- Cao, Z., Ceder, A.A., 2019. Autonomous shuttle bus service timetabling and vehicle scheduling using skip-stop tactic. *Transport. Res. Part C: Emerg. Technol.* 102, 370–395.
- Cao, Z., Yuan, Z., Zhang, S., 2016. Performance analysis of stop-skipping scheduling plans in rail transit under time-dependent demand. *Int. J. Environ. Res. Public Health* 13, 707.
- Cats, O., 2014. Regularity-driven bus operation: Principles, implementation and business models. *Transp. Policy* 36, 223–230.
- Cats, O., 2019. Determinants of bus riding time deviations: Relationship between driving patterns and transit performance. *J. Transport. Eng., Part A: Syst.* 145 (1), 04018078.
- Cats, O., Glück, S., 2019. Frequency and vehicle capacity determination using a dynamic transit assignment model. *Transp. Res. Rec.* 2673 (3), 574–585.
- Cats, O., Larjani, A.N., Koutsopoulos, H.N., Burghout, W., 2011. Impacts of holding control strategies on transit performance: Bus simulation model analysis. *Transp. Res. Rec.* 2216 (1), 51–58.
- Cats, O., Larjani, A.N., Ólafsdóttir, Á., Burghout, W., Andréasson, L.J., Koutsopoulos, H.N., 2012. Bus-holding control strategies: simulation-based evaluation and guidelines for implementation. *Transp. Res. Rec.* 2274 (1), 100–108.
- Cats, O., Rufi, F.M., Koutsopoulos, H.N., 2014. Optimizing the number and location of time point stops. *Public Transport* 6 (3), 215–235.
- Ceder, A., 2007. *Public transit planning and operation: Theory. Modeling and practice.* Elsevier, Oxford.
- Cevallos, F., Zhao, F., 2006a. A genetic algorithm for bus schedule synchronization. In: *Applications of Advanced Technology in Transportation.* pp. 737–742.
- Cevallos, F., Zhao, F., 2006b. Minimizing transfer times in public transit network with genetic algorithm. *Transport. Res. Rec.: J. Transport. Res. Board* 1971, 74–79.
- Chen, C., Chen, W., Chen, Z., 2015a. A multi-agent reinforcement learning approach for bus holding control strategies. *Advances in Transportation Studies.*
- Chen, J., Liu, Z., Zhu, S., Wang, W., 2015b. Design of limited-stop bus service with capacity constraint and stochastic travel time. *Transport. Res. Part E: Logist. Transport. Rev.* 83, 1–15.
- Chen, X., Hellinga, B., Chang, C., Fu, L., 2015c. Optimization of headways with stop-skipping control: a case study of bus rapid transit system. *J. Adv. Transport.* 49 (3), 385–401.
- Chen, X., Yu, L., Zhang, Y., Guo, J., 2009. Analyzing urban bus service reliability at the stop, route, and network levels. *Transport. Res. Part A: Policy Pract.* 43 (8), 722–734.
- Chow, A.H., Li, S., Zhong, R., 2017. Multi-objective optimal control formulations for bus service reliability with traffic signals. *Transport. Res. Part B: Methodol.* 103, 248–268.
- Clement-Nyns, K., Haesen, E., Driesen, J., 2010. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Trans. Power Syst.* 25 (1), 371–380.
- Clotfelter, C., 1993. The private life of public economics. *South. Econ. J.* 59 (4), 579–596.
- Coffey, C., Nair, R., Pinelli, F., Pozdnoukhov, A., Calabrese, F., 2012. Missed connections: quantifying and optimizing multi-modal interconnectivity in cities. In: *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Computational Transportation Science.* ACM, pp. 26–32.
- Corman, F., D'Ariano, A., Pacciarelli, D., Pranzo, M., 2010. A tabu search algorithm for rerouting trains during rail operations. *Transport. Res. Part B: Methodol.* 44 (1), 175–192.
- Cortés, C.E., Jara-Díaz, S., Tirachini, A., 2011. Integrating short turning and deadheading in the optimization of transit services. *Transport. Res. Part A: Policy Pract.* 45 (5), 419–434.
- Cortés, C.E., Sáez, D., Milla, F., Núñez, A., Riquelme, M., 2010. Hybrid predictive control for real-time optimization of public transport systems' operations based on evolutionary multi-objective optimization. *Transport. Res. Part C: Emerg. Technol.* 18 (5), 757–769.
- Daganzo, C.F., 2009. A headway-based approach to eliminate bus bunching: Systematic analysis and comparisons. *Transport. Res. Part B: Methodol.* 43 (10), 913–921.
- Daganzo, C.F., Pilachowski, J., 2011. Reducing bunching with bus-to-bus cooperation. *Transport. Res. Part B: Methodol.* 45 (1), 267–277.
- D'Ariano, A., Corman, F., Pacciarelli, D., Pranzo, M., 2008. Reordering and local rerouting strategies to manage train traffic in real time. *Transport. Sci.* 42 (4), 405–419.
- Delgado, F., Muñoz, J.C., Giesen, R., 2012. How much can holding and/or limiting boarding improve transit performance? *Transport. Res. Part B: Methodol.* 46 (9), 1202–1217.
- Delgado, F., Muñoz, J.C., Giesen, R., Cipriano, A., 2009. Real-time control of buses in a transit corridor based on vehicle holding and boarding limits. *Transport. Res. Rec.: J. Transport. Res. Board* 2090 (1), 59–67.
- Dessouky, M., Hall, R., Zhang, L., Singh, A., 2003. Real-time control of buses for schedule coordination at a terminal. *Transport. Res. Part A: Policy Pract.* 37 (2), 145–164.
- Eberlein, X.J., 1995. *Real-time control strategies in transit operations: Models and analysis.* Ph.D. thesis, Massachusetts Institute of Technology, Department of Civil and Environmental Engineering.
- Eberlein, X.J., 1997. Real-time control strategies in transit operations: Models and analysis. *Transp. Res. Part A* 1 (31), 69–70.
- Eberlein, X.J., Wilson, N.H., Barnhart, C., Bernstein, D., 1998. The real-time deadheading problem in transit operations control. *Transport. Res. Part B: Methodol.* 32 (2), 77–100.
- Eberlein, X.J., Wilson, N.H., Bernstein, D., 2001. The holding problem with real-time information available. *Transport. Sci.* 35 (1), 1–18.
- Fabian, J.J., Sánchez-Martínez, G.E., 2017. Simulation-based comparison of holding strategies for a multibranch light rail service. *Transp. Res. Rec.* 2648 (1), 23–32.
- Fabian, J.J., Sánchez-Martínez, G.E., Attanucci, J.P., 2018. Improving high-frequency transit performance through headway-based dispatching: Development and implementation of a real-time decision-support system on a multi-branch light rail line. *Transp. Res. Rec.* 2672 (8), 363–373.
- Foster, J.M., Trevino, G., Kuss, M., Caramanis, M.C., 2013. Plug-in electric vehicle and voltage support for distributed solar: theory and application. *IEEE Syst. J.* 7 (4), 881–888.

- Fu, L., Liu, Q., Calamai, P., 2003. Real-time optimization model for dynamic scheduling of transit operations. *Transport. Res. Rec.: J. Transport. Res. Board* 1857, 48–55.
- Fu, L., Yang, X., 2002. Design and implementation of bus-holding control strategies with real-time information. *Transport. Res. Rec.: J. Transport. Res. Board* 1791 (1), 6–12.
- Furth, P.G., 1986. Zonal route design for transit corridors. *Transport. Sci.* 20 (1), 1–12.
- Furth, P.G., Day, F.B., 1985. Transit routing and scheduling strategies for heavy-demand corridors (abridgment). *Transportation Research Record* (1011).
- Gao, Y., Kroon, L., Schmidt, M., Yang, L., 2016. Rescheduling a metro line in an over-crowded situation after disruptions. *Transport. Res. Part B: Methodol.* 93, 425–449.
- Gavriilidou, A., Cats, O., 2018. Reconciling transfer synchronization and service regularity: real-time control strategies using passenger data. *Transportmetrica A: Transport Science*, 1–29.
- Gavriilidou, A., Cats, O., 2019. Reconciling transfer synchronization and service regularity: real-time control strategies using passenger data. *Transport. A: Transp. Sci.* 15 (2), 215–243.
- Ghaemi, N., Cats, O., Goverde, R.M., 2017. Railway disruption management challenges and possible solution directions. *Public Transport* 9 (1–2), 343–364.
- Gintner, V., Klierer, N., Suhl, L., 2005. Solving large multiple-depot multiple-vehicle-type bus scheduling problems in practice. *OR Spectrum* 27 (4), 507–523.
- Gkiotsalitis, K., 2019a. Bus rescheduling in rolling horizons for regularity-based services. *J. Intell. Transport. Syst.* 1–20.
- Gkiotsalitis, K., 2019b. Robust stop-skipping at the tactical planning stage with evolutionary optimization. *Transport. Res. Rec.* 2673 (3), 611–623.
- Gkiotsalitis, K., 2020a. Bus holding of electric buses with scheduled charging times. *IEEE Trans. Intell. Transp. Syst.*
- Gkiotsalitis, K., 2020b. A model for the periodic optimization of bus dispatching times. *Appl. Math. Model.* 82, 785–801.
- Gkiotsalitis, K., 2020c. Stop-skipping in rolling horizons. *Transportmetrica A: Transport Science*, 1–29.
- Gkiotsalitis, K., Alesiani, F., 2019. Robust timetable optimization for bus lines subject to resource and regulatory constraints. *Transport. Res. Part E: Logist. Transport. Rev.* 128, 30–51.
- Gkiotsalitis, K., Cats, O., 2019. Multi-constrained bus holding control in time windows with branch and bound and alternating minimization. *Transport. B: Transport Dynam.* 7 (1), 1258–1285.
- Gkiotsalitis, K., Eikenbroek, O.A., Cats, O., 2019a. Robust network-wide bus scheduling with transfer synchronizations. *IEEE Trans. Intell. Transport. Syst.*
- Gkiotsalitis, K., Eikenbroek, O.A., Cats, O., 2020. An exact method for real-time rescheduling after disturbances in metro lines. In: *Transportation Research Board (TRB) 99th Annual Meeting*.
- Gkiotsalitis, K., Stathopoulos, A., 2016. Demand-responsive public transportation re-scheduling for adjusting to the joint leisure activity demand. *Int. J. Transport. Sci. Technol.* 5 (2), 68–82.
- Gkiotsalitis, K., van Berkum, E., 2020a. An analytic solution for real-time bus holding subject to vehicle capacity limits. *Transport. Res. Part C: Emerg. Technol.*
- Gkiotsalitis, K., van Berkum, E., 2020b. An exact method for the bus dispatching problem in rolling horizons. *Transport. Res. Part C: Emerg. Technol.* 110, 143–165.
- Gkiotsalitis, K., Wu, Z., Cats, O., 2019b. A cost-minimization model for bus fleet allocation featuring the tactical generation of short-turning and interlining options. *Transport. Res. Part C: Emerg. Technol.* 98, 14–36.
- Hadas, Y., Ceder, A.A., 2010. Optimal coordination of public-transit vehicles using operational tactics examined by simulation. *Transport. Res. Part C: Emerg. Technol.* 18 (6), 879–895.
- Hans, E., Chiabaut, N., Leclercq, L., 2015a. Investigating the irregularity of bus routes: highlighting how underlying assumptions of bus models impact the regularity results. *J. Adv. Transport.* 49 (3), 358–370.
- Hans, E., Chiabaut, N., Leclercq, L., Bertini, R.L., 2015b. Real-time bus route state forecasting using particle filter and mesoscopic modeling. *Transport. Res. Part C: Emerg. Technol.* 61, 121–140.
- He, S.-X., Liang, S.-D., Dong, J., Zhang, D., He, J.-J., Yuan, P.-C., 2020. A holding strategy to resist bus bunching with dynamic target headway. *Comput. Industr. Eng.* 140, 106237.
- Hernández, D., Muñoz, J.C., Giesen, R., Delgado, F., 2015. Analysis of real-time control strategies in a corridor with multiple bus services. *Transport. Res. Part B: Methodol.* 78, 83–105.
- Hickman, M.D., 2001. An analytic stochastic model for the transit vehicle holding problem. *Transport. Sci.* 35 (3), 215–237.
- Hlotova, Y., Cats, O., Meijer, S., 2014. Measuring bus drivers' occupational stress under changing working conditions. *Transport. Res. Rec.* 2415 (1), 13–20.
- Jamili, A., Aghaee, M.P., 2015. Robust stop-skipping patterns in urban railway operations under traffic alteration situation. *Transport. Res. Part C: Emerg. Technol.* 61, 63–74.
- Jiang, Z., Fan, W., Liu, W., Zhu, B., Gu, J., 2018. Reinforcement learning approach for coordinated passenger inflow control of urban rail transit in peak hours. *Transport. Res. Part C: Emerg. Technol.* 88, 1–16.
- Jordan, W.C., Turnquist, M.A., 1979. Zone scheduling of bus routes to improve service reliability. *Transport. Sci.* 13 (3), 242–268.
- Kepaptsoglou, K., Karlaftis, M., 2009a. Transit route network design problem: Review. *J. Transport. Eng.* 135 (8), 491–505.
- Kepaptsoglou, K., Karlaftis, M.G., 2009b. The bus bridging problem in metro operations: conceptual framework, models and algorithms. *Public Transport* 1 (4), 275–297.
- Khadilkar, H., 2018. A scalable reinforcement learning algorithm for scheduling railway lines. *IEEE Trans. Intell. Transp. Syst.* 20 (2), 727–736.
- Klierer, N., Melloui, T., Suhl, L., 2006. A time-space network based exact optimization model for multi-depot bus scheduling. *Eur. J. Oper. Res.* 175 (3), 1616–1627.
- Klumpenhouwer, W., Wirasinghe, S., 2018. Optimal time point configuration of a bus route—a markovian approach. *Transport. Res. Part B: Methodol.* 117, 209–227.
- Knoppers, P., Muller, T., 1995. Optimized transfer opportunities in public transport. *Transport. Sci.* 29 (1), 101–105.
- Koehler, L.A., Kraus Jr, W., 2010. Simultaneous control of traffic lights and bus departure for priority operation. *Transport. Res. Part C: Emerg. Technol.* 18 (3), 288–298.
- Koehler, L.A., Seman, L.O., Kraus, W., Camponogara, E., 2018. Real-time integrated holding and priority control strategy for transit systems. *IEEE Trans. Intell. Transp. Syst.* 20 (9), 3459–3469.
- Krasemann, J.T., 2012. Design of an effective algorithm for fast response to the re-scheduling of railway traffic during disturbances. *Transport. Res. Part C: Emerg. Technol.* 20 (1), 62–78.
- Laskaris, G., Cats, O., Jenelius, E., Rinaldi, M., Viti, F., 2019. Multiline holding based control for lines merging to a shared transit corridor. *Transport. B: Transp. Dynam.* 7 (1), 1062–1095.
- Laskaris, G., Sredynski, M., Viti, F., 2020. Enhancing bus holding control using cooperative its. *IEEE Trans. Intell. Transp. Syst.* 21 (4), 1767–1778.
- Leffer, D., Cats, O., Jenelius, E., Burghout, W., 2017. Real-time short-turning in high frequency bus services based on passenger cost. In: *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. IEEE, pp. 861–866.
- Leong, W., Goh, K., Hess, S., Murphy, P., 2016. Improving bus service reliability: The Singapore experience. *Res. Transport. Econ.* 59, 40–49.
- Li, J.-Q., 2014. Transit bus scheduling with limited energy. *Transport. Sci.* 48 (4), 521–539.
- Li, J.-Q., Mirchandani, P.B., Borenstein, D., 2008. Parallel auction algorithm for bus rescheduling. In: *Computer-aided Systems in Public Transport*. Springer, pp. 281–299.
- Li, J.-Q., Mirchandani, P.B., Borenstein, D., 2009. A lagrangian heuristic for the real-time vehicle rescheduling problem. *Transport. Res. Part E: Logist. Transport. Rev.* 45 (3), 419–433.
- Li, S., Liu, R., Yang, L., Gao, Z., 2019. Robust dynamic bus controls considering delay disturbances and passenger demand uncertainty. *Transport. Res. Part B: Methodol.* 123, 88–109.
- Li, Y., Gendreau, M., et al., 1991. Real time scheduling on a transit bus route: a 0–1 stochastic programming model.
- Li, Y., Wang, X., Sun, S., Ma, X., Lu, G., 2017. Forecasting short-term subway passenger flow under special events scenarios using multiscale radial basis function networks. *Transport. Res. Part C: Emerg. Technol.* 77, 306–328.
- Lin, G., Liang, P., Schonfeld, P., Larson, R., 1995. Adaptive control of transit operations, final report. Tech. rep., MD-26-7002. US Department of Transportation.

- Liu, H., Skabardonis, A., Zhang, W.-b., 2003. A dynamic model for adaptive bus signal priority. In: 82nd Transportation Research Board Annual Meeting, Washington, DC.
- Liu, Z., Yan, Y., Qu, X., Zhang, Y., 2013. Bus stop-skipping scheme with random travel time. *Transport. Res. Part C: Emerg. Technol.* 35, 46–56.
- Lizana, P., Muñoz, J.C., Giesen, R., Delgado, F., 2014. Bus control strategy application: case study of santiago transit system. *Proc. Comput. Sci.* 32, 397–404.
- Luo, X., Liu, S., Jin, P.J., Jiang, X., Ding, H., 2017. A connected-vehicle-based dynamic control model for managing the bus bunching problem with capacity constraints. *Transport. Plan. Technol.* 40 (6), 722–740.
- Ma, Z., Xing, J., Mesbah, M., Ferreira, L., 2014. Predicting short-term bus passenger demand using a pattern hybrid approach. *Transport. Res. Part C: Emerg. Technol.* 39, 148–163.
- Marguier, P., 1985. Bus route performance evaluation under stochastic conditions. Ph.D. thesis. Massachusetts Institute of Technology, Cambridge, MA.
- Meng, L., Zhou, X., 2014. Simultaneous train rerouting and rescheduling on an n-track network: A model reformulation with network-based cumulative flow variables. *Transport. Res. Part B: Methodol.* 67, 208–234.
- Miles, J., Potter, S., 2014. Developing a viable electric bus service: The milton keynes demonstration project. *Res. Transport. Econ.* 48, 357–363.
- Mirchandani, P.B., Li, J.-Q., Hickman, M., 2010. A macroscopic model for integrating bus signal priority with vehicle rescheduling. *Public Transport* 2 (3), 159–172.
- Mishalani, R.G., McCord, M.R., Forman, S., 2008. Schedule-based and autoregressive bus running time modeling in the presence of driver-bus heterogeneity. In: *Computer-aided Systems in Public Transport*. Springer, pp. 301–317.
- Moreira-Matias, L., Cats, O., 2016. Toward a demand estimation model based on automated vehicle location. *Transp. Res. Rec.* 2544 (1), 141–149.
- Moreira-Matias, L., Cats, O., Gama, J., Mendes-Moreira, J., De Sousa, J.F., 2016. An online learning approach to eliminate bus bunching in real-time. *Appl. Soft Comput.* 47, 460–482.
- Muñoz, J.C., Cortés, C.E., Giesen, R., Sáez, D., Delgado, F., Valencia, F., Cipriano, A., 2013. Comparison of dynamic control strategies for transit operations. *Transport. Res. Part C: Emerg. Technol.* 28, 101–113.
- Nesheli, M.M., Ceder, A., 2017. Real-time public transport operations: Library of control strategies. *Transp. Res. Rec.* 2647 (1), 26–32.
- Nesheli, M.M., Ceder, A.A., Liu, T., 2015. A robust, tactic-based, real-time framework for public-transport transfer synchronization. *Transport. Res. Proc.* 9, 246–268.
- Newell, G.F., 1974. Control of pairing of vehicles on a public transportation route, two vehicles, one control point. *Transport. Sci.* 8 (3), 248–264.
- Nikolaou, M., 2001. Model predictive controllers: A critical synthesis of theory and industrial needs. *Adv. Chem. Eng.* 26, 131–204.
- Obara, M., Kashiyama, T., Sekimoto, Y., 2018. Deep reinforcement learning approach for train rescheduling utilizing graph theory. In: 2018 IEEE International Conference on Big Data (Big Data). IEEE, pp. 4525–4533.
- Osuna, E., Newell, G., 1972. Control strategies for an idealized public transportation system. *Transport. Sci.* 6 (1), 52–72.
- Pangilinan, C., Wilson, N., Moore, A., 2008. Bus supervision deployment strategies and use of real-time automatic vehicle location for improved bus service reliability. *Transp. Res. Rec.* 2063 (1), 28–33.
- Parbo, J., Nielsen, O.A., Prato, C.G., 2014. User perspectives in public transport timetable optimisation. *Transport. Res. Part C: Emerg. Technol.* 48, 269–284.
- Pellegrini, P., Marlière, G., Rodríguez, J., 2014. Optimal train routing and scheduling for managing traffic perturbations in complex junctions. *Transport. Res. Part B: Methodol.* 59, 58–80.
- Phillips, W., del Rio, A., Muñoz, J.C., Delgado, F., Giesen, R., 2015. Quantifying the effects of driver non-compliance and communication system failure in the performance of real-time bus control strategies. *Transport. Res. Part A: Policy Pract.* 78, 463–472.
- Powell, M.J., 2009. The bobyqa algorithm for bound constrained optimization without derivatives. Cambridge NA Report NA2009/06, University of Cambridge, Cambridge, 26–46.
- Puong, A., Wilson, N.H., 2008. A train holding model for urban rail transit systems. In: *Computer-aided systems in public transport*. Springer, pp. 319–337.
- Randall, E.R., Condry, B.J., Trompet, M., Campus, S.K., 2007. International bus system benchmarking: Performance measurement development, challenges, and lessons learned. In: *Transportation Research Board 86th Annual Meeting*, 21st-25th January.
- Richardson, D.B., 2013. Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. *Renew. Sustain. Energy Rev.* 19, 247–254.
- Rizopoulos, D., Saharidis, G.K., 2020. Generic approaches for the rescheduling of public transport services. *Energy Syst.* 1–30.
- Rossetti, M.D., Turitto, T., 1998. Comparing static and dynamic threshold based control strategies. *Transport. Res. Part A: Policy Pract.* 32 (8), 607–620.
- Sáez, D., Cortés, C.E., Milla, F., Núñez, A., Tirachini, A., Riquelme, M., 2012. Hybrid predictive control strategy for a public transport system with uncertain demand. *Transportmetrica* 8 (1), 61–86.
- Sánchez-Martínez, G., Koutsopoulos, H., Wilson, N., 2016. Real-time holding control for high-frequency transit with dynamics. *Transport. Res. Part B: Methodol.* 83, 1–19.
- Sandholm, T., 1993. An implementation of the contract net protocol based on marginal cost calculations. *AAAI* 93, 256–262.
- Saw, V.-L., Vismara, L., Chew, L.Y., 2019. Intelligent buses in a loop service: Emergence of no-boarding and holding strategies. *arXiv preprint arXiv:1911.03107*.
- Seman, L.O., Koehler, L.A., Camponogara, E., Zimmermann, L., Kraus, W., 2019. Headway control in bus transit corridors served by multiple lines. *IEEE Trans. Intell. Transp. Syst.*
- Šemrov, D., Marsetič, R., Žura, M., Todorovski, L., Srdic, A., 2016. Reinforcement learning approach for train rescheduling on a single-track railway. *Transport. Res. Part B: Methodol.* 86, 250–267.
- Shen, S., Wilson, N.H., 2001. An optimal integrated real-time disruption control model for rail transit systems. In: *Computer-aided scheduling of public transport*. Springer, pp. 335–363.
- Sirmatel, I.I., Geroliminis, N., 2018. Mixed logical dynamical modeling and hybrid model predictive control of public transport operations. *Transport. Res. Part B: Methodol.* 114, 325–345.
- Skabardonis, A., 2000. Control strategies for transit priority. *Transp. Res. Rec.* 1727 (1), 20–26.
- Soza-Parra, J., Cats, O., Carney, Y., Vanderwaart, C., 2019. Lessons and evaluation of a headway control experiment in washington, dc. *Transport. Res. Rec.* 2673 (8), 430–438.
- Srinivasaraghavan, S., Khaligh, A., 2011. Time management. *IEEE Power Energ. Mag.* 9 (4), 46–53.
- Strathman, J., Dueker, K., Kimpel, T., Gerhart, R., Turner, K., Taylor, P., Callas, S., Griffin, D., Hopper, J., 1999. Automated bus dispatching, operations control, and service reliability: Baseline analysis. *Transport. Res. Rec.: J. Transport. Res. Board* 1666, 28–36.
- Strathman, J.G., Kimpel, T.J., Dueker, K.J., Gerhart, R.L., Callas, S., 2002. Evaluation of transit operations: Data applications of tri-met's automated bus dispatching system. *Transportation* 29 (3), 321–345.
- Sun, A., Hickman, M., 2004. Scheduling considerations for a branching transit route. *J. Adv. Transport.* 38 (3), 243–290.
- Sun, A., Hickman, M., 2005. The real-time stop-skipping problem. *J. Intell. Transport. Syst.* 9 (2), 91–109.
- Sun, A., Hickman, M., 2008. The holding problem at multiple holding stations. In: *Computer-aided systems in public transport*. Springer, pp. 339–359.
- Sun, D.J., Xu, Y., Peng, Z.-R., 2015. Timetable optimization for single bus line based on hybrid vehicle size model. *J. Traffic Transport. Eng. (English Edition)* 2 (3), 179–186.
- Tang, X., Lin, X., He, F., 2019. Robust scheduling strategies of electric buses under stochastic traffic conditions. *Transport. Res. Part C: Emerg. Technol.* 105, 163–182.
- Teng, J., Chen, T., Fan, W.D., 2020. Integrated approach to vehicle scheduling and bus timetabling for an electric bus line. *J. Transport. Eng., Part A: Syst.* 146 (2), 04019073.
- Toqué, F., Khoudjia, M., Come, E., Trepanier, M., Oukhellou, L., 2017. Short & long term forecasting of multimodal transport passenger flows with machine learning methods. In: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC). IEEE, pp. 560–566.
- Trompet, M., Anderson, R.J., Graham, D.J., 2009. Variability in comparable performance of urban bus operations. *Transp. Res. Rec.* 2111 (1), 177–184.
- Trompet, M., Liu, X., Graham, D., 2011. Development of key performance indicator to compare regularity of service between urban bus operators. *Transport. Res. Rec.: J. Transport. Res. Board* 2216, 33–41.
- Tzeng, G.-H., Lin, C.-W., Opricovic, S., 2005. Multi-criteria analysis of alternative-fuel buses for public transportation. *Energy policy* 33 (11), 1373–1383.

- van Oort, N., Boterman, J., van Nes, R., 2012. The impact of scheduling on service reliability: trip-time determination and holding points in long-headway services. *Public Transport* 4 (1), 39–56.
- Van Oort, N., Wilson, N., Van Nes, R., 2010. Reliability improvement in short headway transit services: Schedule-and headway-based holding strategies. *Transport. Res. Rec.: J. Transport. Res. Board* 2143, 67–76.
- Wang, J., Sun, L., 2020. Dynamic holding control to avoid bus bunching: A multi-agent deep reinforcement learning framework. to appear at *Transportation Research Part C*.
- Wang, Y., Huang, Y., Xu, J., Barclay, N., 2017. Optimal recharging scheduling for urban electric buses: A case study in davis. *Transport. Res. Part E: Logist. Transport. Rev.* 100, 115–132.
- Wang, Y., Ma, W., Yin, W., Yang, X., 2014. Implementation and testing of cooperative bus priority system in connected vehicle environment: case study in taicang city, china. *Transp. Res. Rec.* 2424 (1), 48–57.
- Wen, M., Linde, E., Ropke, S., Mirchandani, P., Larsen, A., 2016. An adaptive large neighborhood search heuristic for the electric vehicle scheduling problem. *Comput. Oper. Res.* 76, 73–83.
- Wood, D., Stasko, T., Tarte, L., Jefferson, D., Reddy, A., 2018. A real-time service management decision support system for train dispatching at New York city transit. *Transp. Res. Rec.* 2672 (8), 327–338.
- Wren, A., Rousseau, J.-M., 1995. Bus driver scheduling—an overview. In: *Computer-aided transit scheduling*. Springer, pp. 173–187.
- Wu, W., Liu, R., Jin, W., 2017. Modelling bus bunching and holding control with vehicle overtaking and distributed passenger boarding behaviour. *Transport. Res. Part B: Methodol.* 104, 175–197.
- Wu, W., Liu, R., Jin, W., Ma, C., 2019. Simulation-based robust optimization of limited-stop bus service with vehicle overtaking and dynamics: A response surface methodology. *Transport. Res. Part E: Logist. Transport. Rev.* 130, 61–81.
- Wu, Y., Yang, H., Tang, J., Yu, Y., 2016. Multi-objective re-synchronizing of bus timetable: Model, complexity and solution. *Transport. Res. Part C: Emerg. Technol.* 67, 149–168.
- Xuan, Y., Argote, J., Daganzo, C.F., 2011. Dynamic bus holding strategies for schedule reliability: Optimal linear control and performance analysis. *Transport. Res. Part B: Methodol.* 45 (10), 1831–1845.
- Yu, B., Yang, Z., Yao, J., 2009. Genetic algorithm for bus frequency optimization. *J. Transport. Eng.* 136 (6), 576–583.
- Yu, Y., Ye, Z., Wang, C., 2015. Study of bus stop skipping scheme based on modified cellular genetic algorithm. In: *CICTP 2015*, pp. 2397–2409.
- Zhao, J., Bukkapatnam, S., Dessouky, M.M., 2003. Distributed architecture for real-time coordination of bus holding in transit networks. *IEEE Trans. Intell. Transport. Syst.* 4 (1), 43–51.
- Zheng, Y., Dong, Z.Y., Xu, Y., Meng, K., Zhao, J.H., Qiu, J., 2014. Electric vehicle battery charging/swap stations in distribution systems: comparison study and optimal planning. *IEEE Trans. Power Syst.* 29 (1), 221–229.
- Zhu, Y., Goverde, R.M., 2020. Dynamic and robust timetable rescheduling for uncertain railway disruptions. *J. Rail Transp. Plan. Manage.* 100196.
- Zolfaghari, S., Azizi, N., Jaber, M.Y., 2004. A model for holding strategy in public transit systems with real-time information. *Int. J. Transp. Manage.* 2 (2), 99–110.