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A review of public transport transfer coordination at the tactical planning phase

Tao Liu [a,b], Oded Cats [c,*], Konstantinos Gkiotsalitis [d]

[a] National Engineering Laboratory of Integrated Transportation Big Data Application Technology, School of Transportation and Logistics, Southwest Jiaotong University, Chengdu 611756, China
[b] Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China
[c] Department of Transport & Planning, Delft University of Technology, the Netherlands
[d] Department of Civil Engineering, Faculty of Engineering Technology, University of Twente, Horst Complex Z222, P.O. Box 217, 7500 AE Enschede, the Netherlands

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ABSTRACT

While transferring between public transport services has a negative impact on the level-of-service, it is an inevitable feature of public transport networks. Transfer coordination can help reduce passenger transfer waiting times and improve service connectivity. In this paper, we systematically review the literature on transfer coordination design in public transport systems. First, four solution approaches for solving the transfer coordination design problem (TCDP) are identified and reviewed in detail, namely heuristic rule-based, analytical modelling, mathematical programming, and simulation. We then identify and review three extensions of the TCDP, i.e., considering first or last train transfer optimization, integrating vehicle scheduling, and incorporating passenger demand assignment. Finally, following the synthesis of the literature, some promising future research directions are outlined. This paper provides comprehensive insights on how to better design coordinated transfers to provide a seamless travel experience and improve the service connectivity of public transport networks.

1. Introduction

Innovations in information and communication technologies, vehicle automation and electrification, along with the emergence of shared mobility, will have a revolutionary impact on future human and freight mobility. Policy makers are aspiring to realize the vision of 'seamless travel' in the next two decades (e.g., LTA Singapore, 2019; OECD, 2020). Empirical studies show that transferring between services has a severe negative impact on users' satisfaction with the service (Susilo and Cats, 2014) as well as on their route choice decisions (e.g., Raveau et al., 2011; Schakenbos et al., 2016; Yap and Cats, 2021). Measures aimed at reducing the negative impact of transfers on the overall journey experience either focus on the subjective user perception of the transfer experience by improving the station environment and information provision (e.g., Chowdhury and Ceder, 2016; Garcia-Martinez et al., 2018) or on reducing the objective (nominal) transfer waiting time (e.g., Ceder, 2016; Daganzo and Anderson, 2016). In this paper, we focus on reviewing past studies aiming at the latter by means of better coordinating the arrivals and departures of connecting services.

The goal of providing well-connected and seamless door-to-door public transport (PT) services to travelers can be addressed by

* Corresponding author.
E-mail address: o.cats@tudelft.nl (O. Cats).

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accommodating transfer considerations into each of the three PT planning levels, i.e., strategic, tactical, and operational levels, as shown in Fig. 1. At the strategic level, a PT agency makes long-term decisions on infrastructure planning, and network design. PT agencies can reduce the number of transfers in the network, optimize the layout of transfer centers to facilitate transfers, and integrate payment methods to increase inter-route or inter-modal service connectivity. At the tactical level, PT agencies can optimize service frequencies and timetables to optimize passenger transfer waiting time. At the operational level, improved vehicle and rolling stock scheduling, and real-time monitoring and control measures, such as vehicle holding, stop-skipping, and rescheduling of vehicles, as well as online travel information provision, can be utilized to increase the actual occurrences of synchronized transfers. This study focusses on reviewing studies at the medium-term, tactical-level timetable coordination design stage in order to improve PT transfer coordination. The planning actions at the tactical level are presented in the middle layer of Fig. 1.

Transfer coordination design is mainly aimed at increasing the connectivity, synchronization, reliability, and accessibility of PT services so as to provide a more attractive and user-centric service. Both bidirectional and unidirectional transfer coordination among different PT routes are considered in the existing studies. In most cases, the synchronization is bidirectional. In some cases, the synchronization is unidirectional. For example, the coordination of last-train transfer is unidirectional; that is, passengers only transfer from one train to the last connecting train. Arguably, missed transfer connections and thereby reduced service reliability and level of service will not only frustrate existing PT users, but also discourage potential new users and depress demand. Well-coordinated transfers can help increase PT patronage and may achieve a modal shift from private car to PT (Chowdhury and Ceder, 2013; Chowdhury et al., 2015). For example, a survey among commuters in the Brussels Capital Region shows that 25% of private car users are willing to shift to PT, if PT transfer connections, along with service speed, availability, timetable and frequency, are enhanced (De Witte et al., 2008). However, measures to improve transfer coordination for PT systems are likely to be worthwhile only in the presence of a large number of transferring passengers and long transfer waiting times, and in the context of low-frequency services where vehicles may wait at transfer stops/stations to allow passengers to have successful transfers. Moreover, measures aimed at improving transfer coordination may induce longer travel times for non-transferring passengers.

The transfer coordination design, which is implemented at the tactical decision-making level, aims at developing a timetable that coordinates the arrival and departure times of PT vehicles at transfer stations so that passengers will have a minimal transfer waiting time or a reliable transfer connection when transferring from one route to another (Castelli et al., 2004; Vuchic, 2005; Ceder, 2016). This can be achieved by employing various tactical-level measures, such as changing the planned departure times of vehicles from the terminal stations, changing service frequencies and headways, and adjusting the planned inter-stop running times and dwell times of vehicles. It is a very difficult optimization problem involving a lot of decision variables and constraints. Furthermore, in practice, there are some stochastic and uncertain factors, such as traffic congestion, irregular passenger arrival patterns, variable and heterogeneous driving patterns among drivers, and random vehicle running and dwell times, which make the optimization problem more complex. Even for the deterministic version, it has been proved to be an NP-Hard (non-deterministic polynomial-time hardness) problem (Ibarra-Rojas and Rios-Solis, 2012). In addition, the optimization of timetables will have an impact on other PT operations-planning activities, such as vehicle scheduling, crew scheduling as well as the route choices made by users. Integrating PT timetable design with other operations-planning activities or passenger assignment models is known to be a cumbersome and time-consuming problem (Shen and Xia, 2009; Ceder, 2016; Schöbel, 2017; Cats and Glück, 2019). Therefore, novel modelling, problem formulations and efficient solution methods should be developed.

Transfer coordination design should be conducted following a systematic approach; that is, to optimize passenger transfer waiting time with a global point of view by also considering other related factors. Some trade-offs should be made when doing transfer coordination optimization. For example, the use of irregular route headways may reduce total passenger transfer waiting time. However,

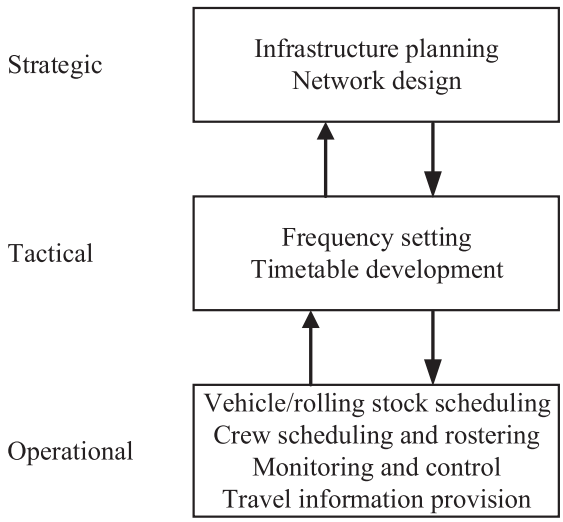

Fig. 1. The three decision-making levels of PT planning and operations, and the related planning/control aspects.

it may lead to an increase of passenger waiting time not only at the transfer stop, but at all downstream boarding stops, or an increase of the fleet size required to maintain the scheduled service. The adjustments of vehicle departure and arrival times at stops may also increase the total in-vehicle travel time of transferring and non-transferring passengers. Thus, the PT transfer coordination optimization problem is a complex multi-criteria optimization problem.

In recent years, we have observed an increasing number of studies on developing solution approaches to address the transfer coordination design problem (TCDP) for transfer optimization purposes. Various solution approaches have been developed, and their analysis and computation results are reported in our literature review. In addition, we identify some interesting and recent trends in extending the TCDP by integrating other PT planning and operation activities to further improve transfer coordination. To facilitate both PT researchers and practitioners to better conduct transfer coordination, a synthesis of the literature and a review of the current state-of-the-art are required. However, to the best of our knowledge, such a comprehensive review is not found in the existing literature. The closest prior art is the literature review of Ibarra-Rojas et al. (2015) on planning, operation, and control of bus transport systems. However, the aforementioned work discussed only briefly the transfer coordination problem while placing more emphasis on bus planning models for strategic, tactical and operational planning.

To bridge this research gap, we conduct a systematic review and synthesize the relevant studies on developing solution approaches to solve the TCDP and its extended problems. Our review is focused on the variants of problem formulations, respective solution approaches, and a critical review of their performances. In this review, we seek to answer the following key questions:

- What kind of solution approaches have been developed to solve the TCDP?
- What is the performance of these solution approaches? What are their advantages and disadvantages?
- What are the emerging research topics in the TCDP domain?
- What are the solution approaches used to solve these emerging topics?
- What are the research gaps and current limitations?
- What are the most promising directions for future research?

The rest of the paper is organized as follows. Section 2 introduces the approach used to conduct the comprehensive literature search and review. A detailed analysis of the identified literature, in terms of the number of papers published in each year, journals, solution approaches, and extended topics, is provided. Section 3 discusses the detailed classification and review of the four solution approaches, i.e., heuristic rule-based, analytical modelling, mathematical programming, and simulation, and the three extension topics, i.e., first or last train transfer optimization, integrating vehicle scheduling, and incorporating passenger demand assignment. Section 4 points out the future research agenda and related research directions. Finally, section 5 concludes the paper.

2. Bibliometric search

We conducted a comprehensive search of the relevant literature by using the databases of Web of Science, Google Scholar, and Scopus. The keywords of public transport, public transit, transit, transfer coordination, transfer synchronization, transfer optimization, transfer connection, schedule coordination, timetable synchronization, timetable coordination, were used when performing the literature search. In addition, we also found relevant papers by checking the references cited in the papers that have already been found. The literature search was completed in October 2021. In the end, a total of 135 papers related to the PT transfer coordination at the tactical planning phase were identified.

Examining the distribution of the 135 papers by the year of publication, we observe that studies of PT transfer coordination can be generally classified into two stages in terms of research output. The first stage, from 1976 to 2013, shows a slow development stage with no more than four papers published per year, followed by a large number of papers published per year from 2014 onwards. It is thus clear that the TCDP has attracted increasing research attention in recent years. This may have resulted from the rapid development of increasingly inter-wined multi-modal PT networks, which require well-connected transfers between different lines, as well as transfer connections between different PT systems. In addition, the recent advancements in data science and high-performance computing technologies enable researchers and practitioners to solve large-scale, real-world PT transfer coordination design problems faster than ever before.

The identified 135 papers were published in a variety of journals, books, and conference proceedings. Analyzing the publication

Table 1
Number of papers of each solution approach and extended topic.

Solution approach	Number of papers
Heuristic rule-based approach	8
Analytical modelling approach	18
Mathematical programming approach	64
Simulation approach	4
Extended PT transfer coordination topic	**Number of papers**
Coordinating first or last train transfers	30
Integrating with vehicle scheduling	6
Incorporating passenger demand assignment	5

venue, the journal of *Transportation Research Part B* published the most papers (14 papers), followed by the *Journal of Advanced Transportation* (11 papers), *Transportation Research Part C* (10 papers), *Transportation Research Record* (9 papers), *Transportation Science* (8 papers).

The 135 papers are further classified into two groups. The first group, with 94 papers, focuses on the core transfer coordination problem; whereas the second group, with 41 papers, extends the TCDP to consider other PT planning and operations activities. The first group of 94 papers is further classified into four categories according to their solution approaches for addressing the TCDP. As shown in Table 1, there are 8 papers using heuristic rule-based approaches, 18 papers using analytical modelling approaches, 64 papers using mathematical programming (MP) approaches, and 4 papers using simulation approaches. We find several papers combing heuristic rule-based and mathematical programming approaches to solve the TCDP. That is, the TCDP is first formulated as a mathematical programming model. Then, heuristic rules are employed to generate initial solutions, which are further optimized by using optimization methods. In this case, we classify the papers into the category of mathematical programming approach. Papers only using heuristic rules are classified into the category of heuristic rule-based approach. From Table 1 we can see that the MP is the most adopted solution approach.

The second group of 41 papers that extend the TCDP can be further classified into three groups, as shown in Table 1. Among them, the first group, which has the most 30 papers, is about the coordination of first or last train transfer connections. The other two extensions, i.e., integrating with vehicle scheduling and incorporating passenger demand assignment, have 6 and 5 papers, respectively. In particular, the TCDP extension that considers the transfer optimization of the first or last train of the day has attracted a lot of research attention. In the next section, we provide a detailed review and critical synthesis of each of the categories identified.

3. Transfer coordination optimization

This section reviews the solution approaches to the TCDP in public transport. We group the solution approaches identified in the literature into four categories, namely (i) the heuristic rule-based approach, (ii) the analytical modelling approach, (iii) the mathematical programming (MP) approach, and (iv) the simulation approach. In addition, the extensions of PT timetable coordination design with other operation planning activities, such as first or last train transfer coordination, vehicle scheduling, and the consideration of passenger assignment are also reviewed. Fig. 2 shows the classification of the TCDP solution methods and the possible extensions.

3.1. Heuristic rule-based solution approach

Early contributions to the field have relied on heuristic rule-based solution methods. Rapp and Gehner (1976) described the use of a computer-aided, coordinated four-stage interactive graphic system for PT timetable coordination design through modifying vehicle departure times at terminals. They adopted a graphical human–computer interactive decision-making process to determine the fleet size for a transit network and reduce the delay of passengers while making transfers. The system was successfully implemented in the Basel Transit System and the implementation results showed that the total passenger transfer delay time can be reduced by approximately 19%. Keudel (1988) also proposed a human–computer dialogue approach using a heuristic optimization process to coordinate a PT timetable in order to minimize the total transfer waiting time. In addition, in the optimization process, Keudel (1988) also

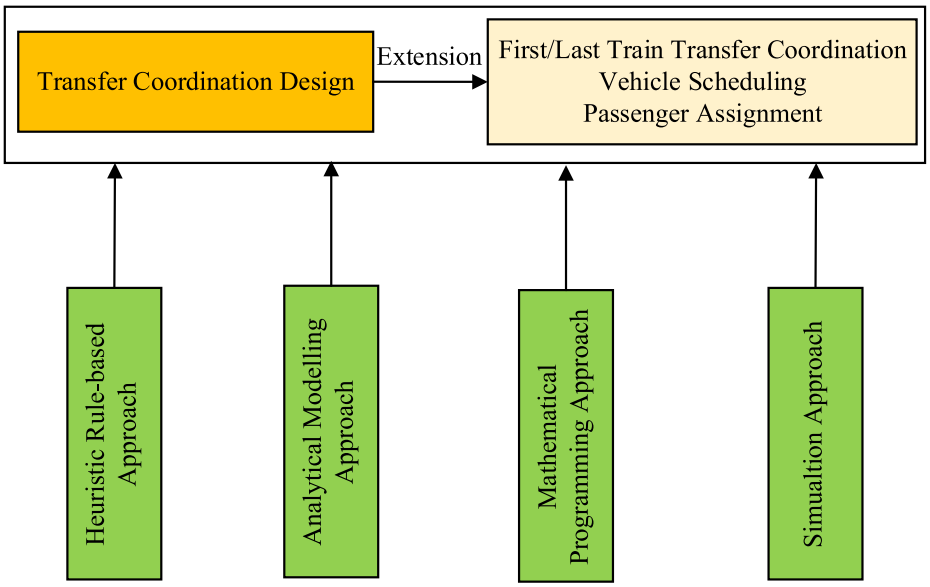

Fig. 2. Extensions of the TCDP and classification of its solution approaches.

considered the minimization of the number of transfer waiting times that exceed a given threshold value. Later developments of graphical approaches include the work of Vuchic et al. (1981) who described a clock-type, diagram-based method to provide graphical representations of timetable coordination designs. Vuchic et al. (1981) proposed the concept of the timed transfer system (TTS) to represent a coordinated timetable for a transit network. They concluded that the application of TTS can achieve more benefits in transfer coordination under several scenarios, such as long service headways, large volumes of transferring passengers, and high route service reliability. Fig. 3 shows an example of a coordinated timetable using the TTS concept. It shows that there are three routes, A, B and C, going through the same transfer stop. Route A has a headway of 15 min, while routes B and C have a headway of 30 min each. Vehicles from all three routes have the same dwell time of 5 min at the transfer stop. Vehicles from the three routes arrive at and depart from the transfer stop simultaneously every 30 min. The graphical methods have the advantage of offering a (potentially compelling) visual representation of the coordinated timetables. They usually require interacting with schedulers who modify the computer-generated timetables to make them more practical and applicable in practice. Fleurent et al. (2004) described the computerized and graphical interactive tools used in the HASTUS scheduling system. In this system, vehicle trip coordination can be visualized and displayed in different graphical views, which can help schedulers further improve the timetable in a scheduler-computer interactive optimization manner.

Another earlier heuristic rule-based approach is to set route headways and modify the dispatching times of the first departing vehicle, also known as *offset times*, to coordinate the arrival and departure times of vehicles at most transfer stops along the network so as to minimize passenger transfer waiting times. Studies using headway as a decision variable usually assume that headways are even. Salzborn (1980) studied a special inter-town trunk route connected by a string of feeder routes. Some intuitive rules were developed to set the offset times of buses on the feeder routes. Brucker and Hurink (1986) investigated the use of elementary number theory to minimize the maximum waiting time for passengers transferring at a single railway transfer station. The simple case of two lines was first considered; then the results were extended into n lines. It concluded that, for railway lines with a fixed headway, the offset times should be set identically to minimize the maximum transfer waiting time. Daganzo (1990) examined the single transfer terminal case and developed some rules for setting the headways of the inbound and outbound routes of a transfer terminal. He showed that the use of integer-ratio headways can achieve an optimal timetable coordination of inbound and outbound routes. He concluded that the use of regular route headways is better for freight transportation systems, and the use of irregular route headways may be better for passenger transportation systems under certain circumstances. Recently, Zhang and Wang (2016) reduced the transfer waiting time between trunk and local buses by simply shifting vehicle departure times. Empirical studies of the New York's capital region demonstrated the effectiveness of this heuristic method in reducing the total transfer waiting time by 34.07%.

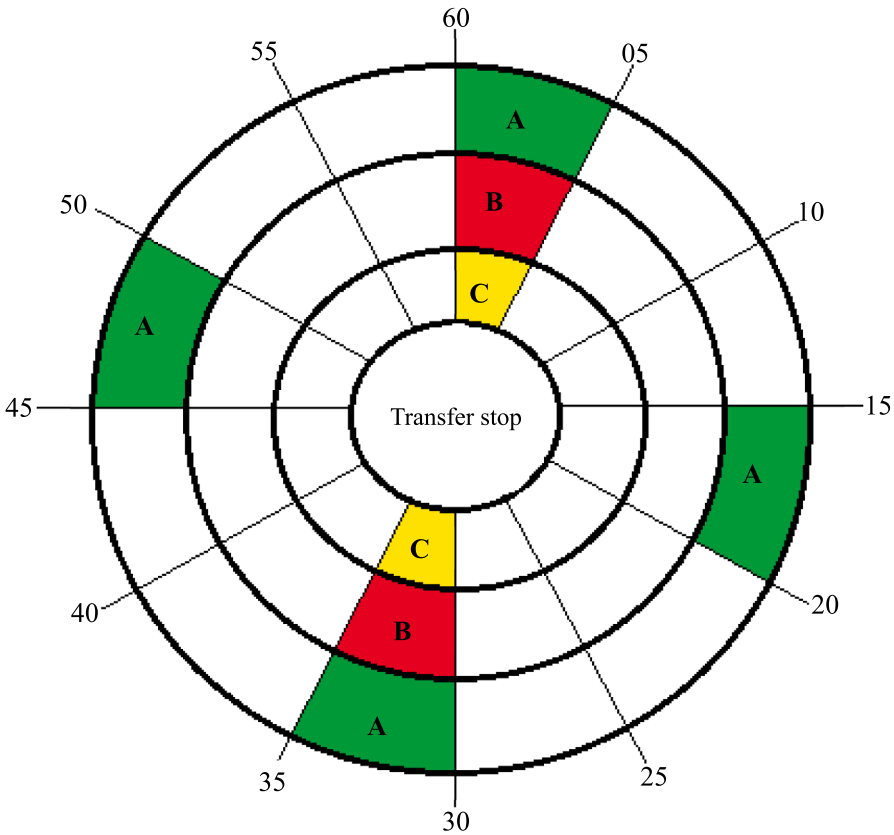

Fig. 3. Illustration of a coordinated timetable using the timed transfer system concept.

Table 2 summarizes the literature review on using heuristic rule-based methods for solving the TCDP. Most studies aim to reduce passenger transfer waiting times, and some studies also consider reducing fleet size as part of their objectives. The most common decision variable considered is the offset time. Some studies also consider changing route headways. All studies used heuristic rules that generally cannot guarantee the optimality of the results. Different problem settings, such as network, trunk-feeder corridor, single transfer terminal, are considered.

3.2. Analytical modelling approach

The analytical modelling approaches develop analytical models for the TCDP. Generally, a total cost function is formulated by considering different cost components – such as operating cost, waiting cost, and transfer cost – with closed-form expressions. The advantage of using analytical modelling approaches is that the optimal design parameters, such as headway, departure time, slack time, and vehicle size can be obtained by minimizing the total cost function with the use of elementary methods of algebra and calculus. A better understanding of the relationship between the design parameters and the total system cost can be achieved by conducting some parameter sensitivity analyses, while requiring fewer computation resources compared to the mathematical programming approaches that need to be solved by optimization solvers.

One of the earliest studies using continuum approximations analytical models for coordinating bus and rail services was conducted by Wirasinghe et al. (1977). Comparing the benefits of using a coordinated bus and rail service with a direct bus service, the authors developed a total benefit function that is a continuous-smooth function. The optimal design variables, including feeder-bus zone boundary, inter-station spacings of the rail line, and train headways, were analytically obtained by using basic calculus. Wirasinghe (1980) further extended the analytical models of Wirasinghe et al. (1977) to consider the case of a coordinated feeder-bus and rail service for a rectangular grid network. By taking the partial derivatives of a total cost function, the closed-form expressions of the design parameters, including the density of feeder bus routes, feeder-bus dispatch rate, and interstation spacing, were obtained.

The pioneering studies of Wirasinghe et al. (1977) and Wirasinghe (1980) have inspired a series of follow-up studies that used the same analytical modelling framework. For example, Lee and Schonfeld (1991) proposed to add slack time into the existing schedule to decrease the probability of missed transfer connections. They considered a simple transit system of a bus line connected with a rail line at a single transfer terminal. A total cost function, including scheduled delay costs, missed connection costs for bus transferring passengers, and missed connection costs for rail transferring passengers, was formulated considering different distributions of bus arrival times. The relationships between the optimal slack times and other parameters, such as headways of buses and trains, transfer passenger volumes, bus operations cost, and standard deviations of buses and trains arrivals, were numerically obtained and analyzed. Moving beyond a single transfer terminal, Chien and Schonfeld (1998) considered a more complex case of a transit corridor with a rapid rail route connected by several feeder bus routes at multiple transfer terminals. A total cost function was formulated by considering the costs of suppliers and users. The decision variables were the station spacing of a rail route, stop spacing of bus routes, headways of both bus and rail routes, bus route spacing, and rail route length. Basic calculus and successive substitution methods were employed to solve the two-dimensional coordination of bus and rail services. Numerical examples were provided, for both the coordinated and uncoordinated cases, to understand the performances of the methodology and solution methods. Chowdhury and Chien (2011) further extended the analytical models by considering joint optimization of bus size, headway, and slack time for the timetable coordination of a transfer hub. For the case of uncoordinated operation, the optimal bus size and headway can be analytically obtained by minimizing the total cost function with the use of basic calculus techniques. Conversely, for the case of coordinated operations, a searching algorithm, named "Powell algorithm" was employed to generate the optimal slack time. A case study of a real-life transit network with two bus lines and one rail line was used to demonstrate the performance of the solution methods. Considering the joint impacts of probabilistic bus arrivals and passenger walking times on transfer coordination, Xiao et al. (2016) further extended the

Table 2
Classification of studies using heuristic rule-based methods for solving the TCDP.

Authors (year)	Objective	Decision variable	Solution method	Problem setting
Rapp and Gehner (1976)	Min transfer delay and fleet size	Offset time	Interactive graphic computer approach	Network, Basel Transit System
Salzborn (1980)	Max number of smooth transfers	Departure and arrival times of feeder routes	Heuristic rules	Trunk-feeder corridor
Brucker and Hurink (1986)	Min maximum waiting time	Offset time	Elementary number theory	Single transfer terminal
Keudel (1988)	Min total transfer waiting time, number of transfer waiting times exceeding a given threshold	Inter-stop travel times	Heuristic optimization process	Network
Daganzo (1990)	Min total system cost	Headway	Heuristic	Single transfer terminal
Fleurent et al. (2004)	Max number of possible transfers	Shifting vehicle departure times	Graphical interactive tools	Network
Vuchic et al. (1981)	Increasing transfer connections	Offset time and headway	Graphical method	Network
Zhang and Wang (2016)	Reducing transfer waiting time	Offset time	Timetable shifting heuristic	Network, New York's Capital District

modelling framework of Chowdhury and Chien (2011). Through a case study for a single transfer station, they found that the probabilistic passenger walking times had a significant impact on the efficiency of transfer connections. When the transfer passenger volume has a significant proportion of the total passenger volume, the optimized slack time significantly impacts the standard deviation of passenger walking times. Recently, Chowdhury and Chien (2019) further considered optimizing the route fare and headway to reduce passenger transfer waiting times. They developed a model to maximize the operator's profit by considering elastic demand. The model was solved by using Powell's iterative search algorithm. The results of a case study for a single transfer terminal showed that a well-coordinated transit system using integer-ratio headways can increase the operator's profit.

There is a group of studies using the analytical modelling approach focused on the transfer coordination between trunk and feeder routes. For coordinating feeder-trunk transfer connection, Goverde (1998) formulated a total expected transfer waiting time cost function, which was a convex function. An optimal buffer time, which was equivalent to the slack time and can be calculated by analytical optimization, was inserted into the schedule to reduce the probability of missed transfer connections. Chowdhury and I-Jy Chien (2002) further investigated the transit corridor feeder-bus and rail coordination by considering stochastic bus arrivals at transfer stations. The total cost function was formulated also considering the user and supplier costs. A four-stage procedure, together with basic calculus, was developed to derive the optimal route headways and slack times. Different degrees of transfer coordination, i.e., full coordination, partial coordination, and no coordination, were defined and analyzed. The results of numerical studies showed that the transfer cost can be reduced by approximately 45%. The results of sensitivity analyses showed that the intermodal transit coordination was beneficial for transit systems with long service headways, low standard variations of vehicle arrival times, and large volumes of transfer passengers. Using continuum approximation models, Sivakumaran et al. (2012) studied the timetable coordination of an idealized trunk-feeder network. The analytical results showed that if the headways of feeder and trunk routes are jointly coordinated, a Pareto-improving result, in terms of reducing the total user cost, feeder operating cost and trunk operating cost, can be achieved. Yang et al. (2020) further considered heterogeneous demand patterns in the trunk-feeder transfer coordination. They proposed a nested two-phase solution algorithm that integrates the analytical optimization method and an adaptive genetic algorithm to generate the optimal coordination design parameters.

One feature of the analytical programing approaches is the use of inter-ratio headways for achieving better timetable coordination. For example, Ting and Schonfeld (2005) employed analytical models to investigate the use of integer-ratio headways for the timetable coordination of a multiple hub transit network. Their results showed that the use of integer-ratio headways was beneficial when transit routes had long headways and large headway variances, which was consistent with the conclusions in Daganzo (1990). In addition, they concluded that transit schedule coordination was not worthwhile when passenger travel demand, especially transfer passenger

Table 3
Classification of studies on using analytical modelling approach for solving the TCDP.

Authors (year)	Objective	Decision variable	Solution method	Problem setting
Wirasinghe et al. (1977)	Increasing total benefits	Feeder-bus zone boundary, interstation spacings, train headway	Basic calculus	Feeder-bus zones connected with a rail trunk
Wirasinghe (1980)	Min total cost	Density of feeder bus routes, dispatch rate, interstation spacing	Basic calculus	Feeder-bus zones connected with a rail trunk
Lee and Schonfeld (1991)	Reducing the probability of missed connections	Slack time	Numerical optimization	Single transfer terminal
Goverde (1998)	Reducing the probability of missed connection	Buffer time	Basic calculus	Trunk-feeder connection
Chien and Schonfeld (1998)	Min total cost	Headway, stop/station-spacing, route spacing, line length	Basic calculus, successive substitution method	Transit corridor with several transfer stations
Chowdhury and I-Jy Chien (2002)	Min total cost	Headway, slack time	Basic calculus, four-stage procedure	Transit corridor with several transfer stations
Ting and Schonfeld (2005)	Min total cost	Headway, slack time	Basic calculus, heuristic algorithm	Small transit networks with two or three transfer stations
Chowdhury and Chien (2011)	Min total cost	Bus size, headway, slack time	Basic calculus, Powell's algorithm	Single transfer terminal
Sivakumaran et al. (2012)	Min generalized cost	Route spacing, stop spacing, frequency	Basic calculus, analytical optimization	Trunk-feeder network
Kim and Schonfeld (2014)	Min total cost	Service type, vehicle size, number of zones, headway, fleet size, slack time	Analytic optimization, numerical methods, genetic algorithm	One terminal connecting multiple regions
Aksu and Akyol (2014)	Min total system cost	Headway, inter-stop travel time	Genetic algorithm	Small network
Xiao et al. (2016)	Min total cost	Slack time, vehicle arrival time at transfer station	Exhaustive search	Single transfer station
Chowdhury and Chien (2019)	Max total profit	Fare, headway	Powell's algorithm, iterative search	Single transfer station
Lai et al. (2020)	Improving the resilience of coordinated timetable	Headway, slack time	Basic calculus	Transit corridor
Yang et al. (2020)	Min total system cost	Headway	Analytical analysis and genetic algorithm	Trunk-feeder corridor
Fan and Ran (2021)	Min total system cost	Headway, stop spacing, number of A/B stops within a skip-stop bay	Calculus of variations, direction search methods	Transit corridor

demand, was low, and the service frequencies were high. Aksu and Akyol (2014) also proposed to use integer-ratio headways for better timetable coordination. A total system cost function was formulated, including operator operating cost, passenger in-vehicle cost, waiting cost, and transfer cost. The optimal integer-ratio headways were generated using a genetic algorithm. Liu and Ceder (2016b) further emphasized the importance of accurate fleet size calculation in formulating the total system cost function, while using integer-ratio headways. Kim and Schonfeld (2014) employed both common headways and integer-ratio headways to integrated fixed-route and flexible-route transit services with timed transfers. An extra transfer cost - consisting of induced slack cost, inter-cycle waiting cost, missed connection cost, and delayed connection cost - was included in the total cost function. A real coded genetic algorithm was employed to generate the optimal design parameters, namely service type, vehicle size, number of zones, headway, fleet size and slack time. Numerical examples for both high-demand and low-demand cases were used to demonstrate the performance of the model and solution methods in reducing the total system cost.

Recently, Lai et al. (2020) extended the work of Ting and Schonfeld (2005) by considering increasing the resilience of coordinated timetables in a transit corridor. A system resilience function was defined to describe the resilience of coordinated timetables in terms of resisting and recovering from passenger flow fluctuations and traffic flow variations. Fan and Ran (2021) incorporated timetable coordination into a skip-stop service planning in a transit corridor with heterogeneous demand patterns. The total system cost function was formulated by considering the transit agency's costs and the users' costs. The optimization model was solved by using calculus of variations and direction search methods. The results of case studies of both rail and bus corridors demonstrated that the inclusion of timetable coordination in skip-stop planning can help further reduce the total system cost, compared to skip-stop planning without timetable coordination. In addition, it found that the use of common headway can achieve the best performance for all tested scenarios.

The review of previous studies on using analytical modelling approaches for solving the TCDP is summarized in Table 3. The objective function of most studies is to minimize the total system cost, which mainly includes the operator cost and the user cost. The transfer waiting time cost is usually included in the user cost. One limitation of the analytical modelling approach is the inaccurate cost component calculation when formulating the total system cost function. Because of using continuum approximations, cost components, such as passenger waiting time and fleet size, receive approximate values that might differ significantly from the actual ones. More accurate estimations of passenger waiting time, transfer waiting time, and fleet size should be subject to further investigation. The decision variables used in most studies are headway, slack time, stop/station spacing, and route spacing. The use of slack time can help increase the probability of successful transfer connections, especially for transfer stations with stochastic vehicle arrivals. However, the addition of slack times may increase the cost of passenger travel delays and the operating cost of operators, i.e., resulting in the common conflict between efficiency and reliability. Thus, a trade-off between increasing the probability of successful transfers and reducing the travel delay and operating cost should be made. Most studies considered both common headways and integer-ratio headways. The demand pattern is often assumed to be fixed (deterministic). Few studies consider elastic demand (stochastic). Earlier studies use only basic calculus techniques to get the optimal decision variables. Recent studies intend to combine basic calculus techniques and numerical optimization methods to better obtain optimal values of decision variables. All the reviewed studies using analytical modelling approaches only considered a single transfer station, a corridor, or a small PT network. There are no studies considering coordinating timetables for large-scale real-world PT networks.

3.3. Mathematical programming approach

Under the mathematical programming (MP) approach, the TCDP is formulated as a MP model. The model can be either deterministic or stochastic. Exact optimization techniques, or heuristic and meta-heuristic algorithms are usually employed to solve MP models. Heuristic algorithms usually use a specific set of rules to address the MP models. There are several commonly used classes of meta-heuristic algorithms such as neighborhood search (e.g., simulated annealing and tabu search), evolutionary search (e.g., genetic algorithm), and hybrid search that combines multiple solution methods (Guihaire and Hao, 2008). Exact optimization techniques can always provide an optimal solution, while heuristic and meta-heuristic algorithms cannot guarantee a globally optimal solution.

Some studies reviewed in the above analytical modelling approach section also formulated the TCDP as a MP model. The main difference between these studies and the studies reviewed in this section is that some parameters or decision variables, such as passenger demand, headway, stop/station spacing, and line spacing, are usually treated as approximated smooth, continuous functions under the analytical modelling approach, while they are mostly treated as accurate variables taking discrete values under the MP approach. As pointed out by Sivakumaran et al. (2012), models using continuum approximations have the advantage of providing closed-form solutions with less computational requirements, while models using discrete parameters and variables have the advantage of generating more realistic results.

In this section, we review studies using MP models with discrete variables to conduct PT transfer coordination design. We classify the related studies into three categories, namely (i) studies using exact solution methods, (ii) studies using heuristic or meta-heuristic solution methods for deterministic MP models, and (iii) studies using heuristic or meta-heuristic solution methods for stochastic or uncertain MP models.

3.3.1. Exact solution methods

There is a group of studies employing exact solution methods for PT timetable coordination design. Domschke (1989) developed a branch and bound (B&B) algorithm that can generate exact solutions for small PT networks. For small networks with 8, 10, and 14 routes, the branch and bound algorithm can generate exact solutions in 30 s, 8 min and 35 h, respectively. While for networks with 16 routes. At the time it took the algorithms about two days to generate the solution. The author concluded that it is impossible to attain exact solutions for large-scale problems using the B&B algorithm within an acceptable computation time. By introducing a binary

variable, Schröder and Solchenbach (2006) reformulated the quadratic semi-assignment problem model of Klemt and Stemme (1988) and Domschke (1989) as an integer linear programming (ILP) model, which can be solved by using a commercial solver, such as CPLEX. Ibarra-Rojas and Rios-Solis (2012) also showed that the B&B algorithm can find exact optimal solutions for networks with up to 10 lines in a computation time of ten hours. Saharidis et al. (2014) formulated a mixed-integer programming (MIP) model to minimize the total transfer waiting time. Transfer stations with large volumes of transferring passengers are given priority by adding weights into the objective function. The model was solved with CPLEX. For small size networks, it can generate the optimal results within a reasonable computation time. Dou et al. (2015) also used CPLEX to solve a mixed-integer linear programming (MILP) model for the timetable coordination of a bus-train bi-modal network. By modifying the offset times of the original timetable, it aimed at maximizing the number of smooth transfers between bus and MRT system in Singapore. Fouilhoux et al. (2016) extended the work of Ibarra-Rojas and Rios-Solis (2012) by adding valid inequalities, which can reduce the complexity of the model. The reduced model was solved by using CPLEX. Recently, Tian and Niu (2017) employed a dynamic programming method to coordinate timetables at a rail transfer station with the objectives of maximizing the number of successful transfers and minimizing slack times. Wu et al. (2018) also aimed at maximizing the number of passengers making successful transfers. A MIP model was developed and solved by using a B&B algorithm after a preprocessing. Takamatsu and Taguchi (2020) employed an event-activity network approach, which is similar to the time–space network approach, for coordinating bus-train transfers in low-frequency areas. The problem was formulated as a MIP model with the objective of maximizing the time gains of transfer passengers minus the losses induced upon direct passengers that do not perform any transfers. Recently, Estrada et al. (2021) considered optimizing a transit corridor shared by two branched routes. The objective is to minimize the total user and agency costs, including initial waiting, transferring waiting and in-vehicle travel times, fleet size, vehicle kilometers traveled, and variations of headways. Two transfer types were considered in the model formulation. The IP model was solved by using a grid search method. They proposed to combine route headway and offset time optimization with the use of control strategies. Case study results of a transit corridor in Barcelona showed that the route service regularity can be improved and the total cost can be reduced by 5%, by combining with the utilization of adding slack time at control stops and transit signal priority strategies.

The review of studies using exact solution methods of MP approach to PT transfer coordination design is summarized in Table 4. All the studies formulate the problem as an integer program (IP) or MIP using vehicle departure times from the terminal stations as decision variables. A few studies also use vehicle dwell times, inter-stop travel times, and route headways as decision variables. The models exhibit diversity in their objective function formulation, including minimizing total transfer waiting times, maximizing the number of synchronizations, and maximizing the number of successful transferring passengers. Most studies use a B&B algorithm, or the commercial optimization solver CPLEX. However, B&B is usually used to solve small size problems. More efficient algorithms that can solve large-scale real-world problems are required.

3.3.2. Heuristic or meta-heuristic solution methods for deterministic mathematical programming models

In order to solve large-scale real-world TCDPs, many studies have focused on developing heuristic or meta-heuristic solution methods that can generate a well-coordinated timetable within an acceptable computation time. The pioneering works of Klemt and Stemme (1988) and Domschke (1989) developed a 0–1 IP model, named quadratic semi-assignment model, for the PT timetable synchronization design problem, which is a special case of the quadratic programming model. The model aims to minimize the total

Table 4
Classification of exact solution methods of the mathematical programming approach to the TCDP.

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Domschke (1989)	Min total transfer waiting time	Offset time	0–1 IP model	B&B algorithm	West-Berlin's subway network with six routes
Schröder and Solchenbach (2006)	Min total transfer penalty	Offset time	ILP model	CPLEX	Network of city buses and regional trains in Kaiserslautern
Ibarra-Rojas and Rios-Solis (2012)	Max number of synchronizations, reducing bunching	Departure time	IP model	B&B algorithm	Randomly generated numerical networks
Saharidis et al. (2014)	Min total transfer waiting time	Departure time	MIP Model	CPLEX	Bus network of the Greek island of Crete
Dou et al. (2015)	Max number of smooth transfers	Offset time, travel time	IP model	CPLEX	Bus and MRT system in Singapore
Fouilhoux et al. (2016)	Max weighted sum of synchronized transfers	Departure time	IP model	CPLEX	Randomly generated numerical networks
Tian and Niu (2017)	Max number of successful connections, Min connection slack time	Departure/ arrival times, dwell time	NLIP model	Dynamic programming	A rail transfer station
Wu et al. (2018)	Max number of passengers making successful transfers	Departure/ arrival times	MIP model	B&B algorithm	Small numerical example network
Takamatsu and Taguchi (2020)	Max gain of transfer passengers minus the loss of direct passengers	Departure/ arrival times	MIP model	CPLEX	Bus network in the Tohoku District of Japan
Estrada et al. (2021)	Min user and agency costs	Offset time, headway	IP model	Grid search, enumeration	Corridor served by two branched routes in Barcelona

Note: IP = integer programming, ILP = integer linear programming, NLIP = nonlinear integer programming.

passenger transfer waiting time. Klemt and Stemme (1988) developed a nearest neighbor search heuristic algorithm to solve the optimization model. For real-world PT networks with less than 100 transfer stations, the heuristic algorithm can generate a high-quality solution with an average gap of 12% from the optimal solution in less than one minute. Domschke (1989) developed three heuristic algorithms, namely a regret method, improvement algorithm, and simulated annealing (SA), to solve the optimization model. The computation results for a six-route subway network showed that the proposed heuristic algorithms have good performance in terms of improving solution quality and reducing computation time. Voß (1992) and Daduna and Voß (1995) further extended the model of Klemt and Stemme (1988) and Domschke (1989) by reformulating the model with a new objective of minimizing the maximum transfer waiting time. In addition, Voß (1992) considered reducing vehicle bunching at commonly used line segments, i.e., common lines. The tabu search algorithm was proposed for solving the models. Numerical results using randomly generated data showed that the tabu search algorithm had a better performance, compared to the SA algorithm proposed in Domschke (1989). The model of Klemt and Stemme (1988) and Domschke (1989) was further extended in Adamski and Bryniarska (1997) and Adamski and Chmiel (1997) by considering coordinating buses at common route segments. The objective function was modified by considering reducing the variance of headways. Schüle et al. (2009) further extended the model of Voß (1992) by considering different objective functions. Instead of minimizing total waiting time, a waiting time at transfer stop was assigned a corresponding penalty value and the main objective is to minimize the total penalties. In addition, two objectives, i.e., minimizing the worst case and minimizing the changes made to the existing timetable, were considered. The multi-criteria optimization model was solved by using three meta-heuristics, i.e., ant colony optimization, evolutionary algorithm, and SA.

With the objective of maximizing the total number of simultaneous arrival of buses at transfer stations in a PT network, Ceder et al. (2001) and Ceder and Tal (2001) developed another MIP model. The decision variables are the departure times of buses from terminals. Different from previous studies, the headways are not fixed and can vary between given time intervals. A heuristic algorithm was developed to solve the model. Several numerical examples, along with a real-life case study, were employed to show the performance of the heuristic solution algorithm.

To quantify the number of successful transfers at a transfer station, a binary synchronization variable is defined by the following two equations, which is widely used in the literature (e.g., Ceder et al., 2001; Ibarra-Rojas and Rios-Solis 2012; Wu et al., 2015; Fouilhoux et al., 2016; Wu et al., 2016; Ibarra-Rojas et al., 2016; Cao et al., 2019).

$$(x_{ip} + t_{ipn}) - \left(x_{jq} + t_{jqn}\right) \geq w_n - M(1 - y_{ipjqn}) \tag{1}$$

$$(x_{ip} + t_{ipn}) - \left(x_{jq} + t_{jqn}\right) \leq W_n + M(1 - y_{ipjqn}) \tag{2}$$

where x_{ip} is the vehicle departure time of trip p of route i, x_{jq} is the vehicle departure time of trip q of route j, t_{ipn} is the vehicle travel time of trip p of route i from the departure terminal to transfer station n, t_{jqn} is the vehicle travel time of trip q of route j from the departure terminal to transfer station n, w_n and W_n are the minimal and maximal transfer times required for ensuring a successful transfer, M is a large positive constant, and y_{ipjqn} is a binary variable, called binary synchronization variable. If the difference between the arrival times of the p-th vehicle of route i and the q-th vehicle of route j is within the specified time window $[w_n, W_n]$, then the binary synchronization variable is activated and equal to one, otherwise it is zero. Thus, Eqs. (1) and (2) together define whether the transfer from trip p of route i to trip q of route j is feasible or not. Except for maximizing the number of successful transfers, another commonly used objective function is to maximize the total number of passengers who can successfully make transfers. This is usually done by multiplying the number of transferring passengers N_{ipjqn} with a binary synchronization variable y_{ipjqn} (e.g., Shafahi and Khani, 2010; Fouilhoux et al., 2016; Wu et al., 2016).

The seminal work of Ceder et al. (2001) inspired a series of follow-up studies. Most studies focused on improving the model formulation. For example, Liu et al. (2007) extended the model of Ceder et al. (2001) by incorporating two coefficients, namely a weighting coefficient and a synchronization coefficient, into the objective function. A tabu search algorithm was proposed to solve the new model. Shi et al. (2007) also modified the objective function of the model in Ceder et al. (2001) by including a second objective function, which intends to maximize the number of vehicles arriving simultaneously at transfer stops. However, this may increase the curbside or the terminal parking requirement. Jansen et al. (2002) modified the objective function by considering the weighted total transfer waiting time. A tabu search heuristic algorithm was proposed to solve the model. The model and algorithm were tested by using a PT network adapted from the greater Copenhagen metropolitan area. Shafahi and Khani (2010) extended the model of Ceder et al. (2001) by reformulating the objective function so as to minimize the total transfer waiting time, instead of maximizing the total number of simultaneous arrivals of vehicles at transfer stops. In addition, they considered the extra stopping time of vehicles at transfer stops, which is equivalent to the slack time used in the analytical modelling approaches, to increase the probability of successful transfers. For small and medium-sized PT networks, the model can be solved by using commercial optimization solvers, such as CPLEX. While for large-scale size problems, a GA was proposed for solving it. Nasirian and Ranjbar (2017) proposed to use a scatter search algorithm to solve a MILP model for minimizing the total passenger transfer waiting time. Computation experiments based on both small numerical example networks taken from Ceder et al. (2001), and Shafahi and Khani (2010), and the Tehran urban railway network (TURN) showed that the scatter search algorithm has better performance and can reduce the total passenger transfer waiting time of the TURN by 56%. Ibarra-Rojas and Rios-Solis (2012) extended the model of Ceder et al. (2001) by reformulating the synchronization constraints using a binary synchronization variable. In addition, except for maximizing the synchronizations, it also considered reducing vehicle bunching. A multi-start iterative local search algorithm was proposed for solving the model after doing a preprocessing to reduce the number of decision variables and constraints. Ibarra-Rojas et al. (2016) further extended the model to consider the multi-period operation. Wu et al. (2016) further extended the work of Ibarra-Rojas and Rios-Solis (2012) by including the

number of transferring passengers in the objective function. In addition, another objective function of minimizing schedule deviation after re-scheduling was considered. The bi-objective optimization model was solved by using a non-dominated sorting genetic algorithm II (NSGA II). Cao et al. (2019) extended the model of Ceder et al. (2001) by allowing permissible and flexible transfer waiting times, and considered the importance of lines and transfer stations, which is also considered in Guo et al. (2016). A MIP model was formulated to maximize the simultaneous arrivals of trains at transfer stations within a time window. The model was solved by using a tailored genetic algorithm combined with a local search heuristic strategy. Recently, Hu et al. (2019) extended the model to a bi-level programming model. The upper level minimizes the travel time of passengers on transfer paths, while the lower level maximizes the number of simultaneous vehicle arrivals at transfer stations. Abdolmaleki et al. (2020) reformulated the model as an IP model with congruence constraints. Their reformulated model includes a well-known maximum direct cut subproblem, which can be solved using an approximation algorithm and local search methods.

Except for synchronizing transfers at a transfer station, there are also some studies aiming to synchronize transfers at common stops or over-lapping route segments. For example, Ibarra-Rojas and Muñoz (2016) considered synchronizing transfers between different lines at common stops or overlapping route segments. A penalty was defined to describe the deviation from the desirable arrival time interval. The objective function was to minimize the sum of weighted penalties. Silva-Soto and Ibarra-Rojas (2021) further developed a bi-objective MILP optimization model for synchronizing a group of bus lines that have overlapping route segments and share common stops. Recently, Wang et al. (2021) developed a bi-level programming model to optimize the transfer connection between a rail transit line and its bridging buses when operation disruptions are happened in the rail transit. The model was solved by using an improved SA algorithm, combined with a heuristic algorithm. Case study results of the Shanghai Rail Transit Line 10 showed that the passenger waiting time can be reduced by 14% and the number of failed transfers can be reduced by 55%.

Through modifying an existing timetable by shifting vehicle departure times at terminal stations, Nachtigall and Voget (1996) proposed to use a GA, combined with a greedy heuristic and a local improvement procedure to minimize the total passenger transfer waiting time in the German railway network. Nachtigall and Voget (1997) further reformulated their model as a bi-objective optimization model by considering a second objective of reducing investment cost incurred by the reduction of train running time. The new model was solved by a hybrid GA including fuzzy logic. Cevallos and Zhao (2006) and Poorjafari et al. (2014) also developed IP models to reduce the total passenger transfer waiting times in PT networks. Cevallos and Zhao (2006) proposed a GA to solve the model, while Poorjafari et al. (2014) proposed to use a SA. The GA was tested for a PT network consisting of 40 routes and 225 transfer stations from Broward County Transit in Florida. It led to a 13% reduction in total transfer waiting time. The SA was tested on a small network with three bidirectional lines and two transfer stations. Xiong et al. (2015) also considered shifting vehicle departure times when optimizing transfer connections between shuttle routes and subway routes. They proposed combining the shifting departure time heuristic with the Frank–Wolfe algorithm. They concluded based on case study results of a network of four shuttles routes connecting to three subway stations in Beijing that the combined algorithm performs better than a GA. The total passenger transfer cost can be reduced by 54%. Tuzun Aksu and Yılmaz (2014) also employed a GA to analyze the trade-off between reducing transfer waiting times and initial waiting times when using heterogeneous headways for transit timetable coordination. Shen and Wang (2015) and Tian et al. (2018) proposed a particle swarm optimization (PSO) algorithm to maximize the number of simultaneous arrivals of vehicles in PT networks. Niu et al. (2015) developed a NLIP model to synchronize the high-speed railway timetables. For the case of two lines, the model was solved by using a GA. Aiming to optimize transfer waiting time for transferring passengers, Gkiotsalitis and Maslekar (2018) considered the impacts of timetable modification on the excess waiting time of passengers at non-transfer stops. A NLIP model was formulated to minimize the weighted transfer waiting time and excess waiting time. The model was first transformed into an unconstrained optimization model by using an exterior point penalty function; then it was solved by using a sequential hill-climbing heuristic method to approximate global optimum solutions. Case study results from bus lines in Stockholm showed that the transfer waiting time can be reduced by 13%. Liu et al. (2018) proposed a simulated annealing (SA) algorithm with parallel computing to minimize the total transfer waiting time in a metro network. The passenger flow was estimated from an automatic fare collection system. Wu et al. (2019) modified the initial vehicle departure times to maximize the number of successful transfer passengers. The problem was formulated as a NLIP and a GA with local search was proposed to solve it. Nesmachnow et al. (2020) used an evolutionary algorithm, which is similar to a GA, to solve the bus timetable synchronization problem.

Except for changing the departure times of vehicles, some studies also considered other decision variables, such as changing inter-stop running times, dwell times, and turnaround layout times. Wong et al. (2008) formulated a MIP model using vehicle departure times, dwell times, run times and turnaround times as decision variables of the optimization model. The model was very complex because of the inclusion of various binary and integer variables and constraints. An optimization-based heuristic method was developed to solve the model. A case study of the Hong Kong Mass Transit Railway network showed that after implementing the optimization method the average transfer waiting times of passengers can be reduced by 41% and 43% for the rush-hour period and non-rush-hour-period, respectively. Kwan and Chang (2008) also considered changing headways, dwell times, run times, and turnaround times. Two optimization functions were defined. One is to minimize the total passenger dissatisfaction index, and the other is to minimize the total schedule deviation index. The NSGA II, combined with some local search heuristics, was proposed to solve the bi-objective optimization model. Computation results showed that the combined NSGA II and multi-objective evolutionary algorithm with local search techniques had better performance in terms of convergence and computation efficiency. From an equity perspective, Wu et al. (2015) minimized the worst weighted transfer waiting time in a subway network by adjusting the departure time, running time and headways of trains. The proposed min–max IP model was solved using a GA. Taking offset times, dwell times, running times, headways of routes as decision variables, Liu and Ceder (2016a) further considered using vehicle size as a decision variable. They developed a bi-objective IP model with route offset time, headway, and vehicle size as decision variables. The first objective was to minimize the discrepancy between observed passenger load and desired occupancy level on a vehicle at its maximum load point. The

Table 5
Classification of heuristic or meta-heuristic solution methods of the deterministic mathematical programming approach to the TCDP.

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Klemt and Stemme (1988)	Min total transfer waiting time	Offset time	0–1 IP model	Heuristic algorithm, nearest neighbour search	West-Berlin underground network
Domschke (1989)	Min total transfer waiting time	Offset time	0–1 IP model	Regret methods, improvement algorithm, SA	West-Berlin's subway network
Voß (1992)	Min total transfer waiting time, maximum transfer waiting time	Offset time	0–1 IP model	Meta-heuristic algorithm, TS	Numerical example network
Daduna and Voß (1995)	Min total transfer waiting time, maximum transfer waiting time	Offset time	0–1 IP model	TS	Public transport networks in German cities
Nachtigall and Voget (1996)	Min total transfer waiting time	Offset time	IP model	GA, greedy heuristic	Randomly generated and German railway networks
Nachtigall and Voget (1997)	Min total transfer waiting time, investment cost	Offset time	Bi-objective IP model	Hybrid GA, fuzzy logic	German railway networks with 28 lines
Adamski and Chmiel (1997)	Min total transfer waiting time, headway deviation	Offset time	0–1 IP model	GA	Small numerical example network
Adamski and Bryniarska (1997)	Min total transfer waiting time, headway deviation	Offset time	0–1 IP model	TS, GA	Small numerical example network
Ceder et al. (2001)	Max the number of simultaneous arrivals of vehicles	Departure times of buses	MILP model	Heuristic algorithm	Example network, bus network in Israel
Ceder and Tal (2001)	Max the number of simultaneous arrivals of vehicles	Departure times of buses	MILP model	Heuristic algorithm	Example network
Shrivastava and Dhingra (2002)	Min total cost	Frequencies and timings of trains and buses	IP model	GA	Trunk-feeder bus network in Mumbai
Shrivastava et al. (2002)	Min total cost	Frequencies and timings of trains and buses	IP model	GA	Trunk-feeder bus network in Mumbai
Jansen et al. (2002)	Min weighted total transfer waiting time	Departure times, connection variables	IP model	TS	Network in Copenhagen
Shrivastava and O'Mahony (2006)	Min total cost	Frequencies and timings of trains and buses	IP model	GA	Trunk-feeder bus network in Mumbai
Cevallos and Zhao (2006)	Min total transfer time	Offset times	IP model	GA	Network in Broward County, Florida
Liu et al. (2007)	Max the number of simultaneous arrivals of vehicles	Departure times of buses	MILP model	TS	Small numerical example network
Shi et al. (2007)	Max the number of simultaneous arrivals of vehicles, number of vehicles arriving simultaneously at transfer stops	Departure times of buses	MILP model	Heuristic algorithm	Small numerical example network
Schüle et al. (2009)	Min total transfer penalty, worst result, changes	Offset times	0–1 IP model	ACO, evolutionary algorithm, SA	Network in south-western Germany
Wong et al. (2008)	Min total transfer waiting time	Offset times, dwell times, run times, turnaround times	MILP model	Optimization-based heuristic	Mass Transit Railway network in HK
Kwan and Chang (2008)	Min total passenger dissatisfaction index, total deviation index	Headways, dwell times, run times, turnaround times	Bi-objective IP model	NSGA II, local search	Network adapted from Singapore MRT and bus systems
Shafahi and Khani (2010)	Min total transfer waiting time	Offset times, extra stopping times	MILP model	Commercial solver, GA	Numerical network, Mashhad City bus network
Ibarra-Rojas and Rios-Solis (2012)	Max number of synchronizations, reducing bunching	Departure times	IP problem	Multi-start iterated local search	Networks with up to 200 lines
Poorjafari et al. (2014)	Min total transfer waiting time	Offset times	IP problem	SA	Small numerical example network
Tuzun Aksu and Yılmaz (2014)	Min total waiting time and number of missed transfer connections	Departure times of vehicles	IP problem	GA	Rail transit network in Istanbul
Niu et al. (2015)	Min waiting time, crowding disutility	Departure/ arrival times	NLIP model	Dynamic programming algorithm, GA	One line, two lines
		Departure times	IP model	PSO	

(*continued on next page*)

Table 5 (*continued*)

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Shen and Wang (2015)	Max number of simultaneous arrivals				Numerical networks and network in Wuhan
Wu et al. (2015)	Min worst weighted transfer waiting time	Departure time, running time, headway	Min-max IP model	GA	Subway network in Beijing
Xiong et al. (2015)	Min transfer cost, schedule delay, overloading penalty	Departure time	IP model	GA, Frank–Wolfe algorithm, heuristic	Network of four shuttles routes connecting to three subway stations in Beijing
Ibarra-Rojas et al. (2016)	Max number of simultaneous arrivals	Departure times	ILP model	Multistart iterated local search algorithms, multistart VNS, population-based algorithm	Numerical testing networks
Wu et al. (2016)	Max number of passengers making successful transfers, Min schedule deviation	Departure times	Bi-objective IP model	NSGA	Bus network in Shenyang, China
Ibarra-Rojas and Muñoz (2016)	Min sum of weighted penalties	Departure times	IP model	Biased random key GA	Network in Santiago, Chile
Liu and Ceder (2016a)	Min waiting time, load discrepancy	Offset time, headway, vehicle size	Bi-objective IP model	Heuristic decomposition method	Example network, network in Auckland
Guo et al. (2017)	Max number of synchronizations	Departure/ arrival times, running/ dwell times, headway	MINLP model	PSO, SA	Beijing metro network
Nasirian and Ranjbar (2017)	Min total transfer waiting time	Headway	MILP	CPLEX, scatter search algorithm	Testing network, Tehran Urban Railway Network
Gkiotsalitis and Maslekar (2018)	Min transfer waiting time, excess waiting time	Departure times	NLIP model	Sequential hill-climbing heuristic method	Bus lines in Stockholm
Liu et al. (2018)	Min total transfer waiting time	Offset times	IP model	SA with parallel computing	Shenzhen metro network
Shang et al. (2018)	Min total travel time	Offset times, dwell times, running times, headway	MIP model	GA	Beijing subway network
Tian and Niu (2019)	Max number of connections, Min total transfer waiting time	Departure/ arrival times, dwell times	Bi-objective IP model	Heuristic algorithm	Sub-network of Chinese high-speed railway network
Cao et al. (2019)	Max number of simultaneous arrivals	Departure times	MIP model	GA, local search	Numerical and Beijing subway networks
Hu et al. (2019)	Max number of simultaneous arrivals, Min travel time	Departure times	Bi-level programming model	Heuristic algorithm	Small numerical example network
Nesmachnow et al. (2020)	Max number of passengers having successful transfers	Offset time	MIP model	Evolutionary algorithm	Network in Montevideo, Uruguay
Wang et al. (2020)	Min passenger waiting time, transfer failure penalty	Departure/ arrival times	MIP model	GA, grey wolf optimizer	Numerical network, Shenyang rail transit network
Abdolmaleki et al. (2020)	Min total transfer waiting time	Offset time	IP model	Approximate algorithm, local search	Example network, Mashhad city bus network
Yin et al. (2021)	Min level of crowdedness at stations	Departure time, number of waiting/ boarding passengers	MILP model	Adaptive large neighbourhood search algorithm, CPLEX	Beijing metro network
Silva-Soto and Ibarra-Rojas (2021)	Min waiting time, operating cost	Departure time	MILP model	Biased random-key GA, hierarchical NSGA	Numerical testing networks
Wang et al. (2021)	Min transfer waiting and failure costs, vehicle usage and energy consumption costs	Bus departure times and route	Bi-level programming model	Improved SA, heuristic algorithm	Shanghai Rail Transit Line 10 with bridging buses

Note: IP = integer programming, MILP = mixed integer linear programming, MIP = mixed integer programming, NLIP = nonlinear integer programming, ILP = Integer linear programming, SA = simulated annealing, GA = genetic algorithm, TS = tabu search, ACO = ant colony optimization, PSO = particle swarm optimization, VNS = variable neighborhood search.

second objective was to minimize the total passenger waiting time, including the waiting time at boarding stops and the transfer waiting time at transfer stops. The model was solved by using a heuristic decomposition method.

Considering the variation of passenger demand during the transition period from peak hours to off-peak hours or vice versa, Guo et al. (2017) developed a MINLP model to maximize the number of synchronizations of the Beijing metro network. A hybrid meta-heuristic algorithm by integrating the PSO and SA was developed to solve the MINLP model. Shang et al. (2018) developed a MIP model to minimize the total travel time of a subway network. The model, considering time-dependent passenger demand, was solved by using a GA combined with a binary variable determination method. Tian and Niu (2019) developed a bi-objective optimization model to maximize the number of successful transfer connections and minimize the total transfer waiting time. A heuristic search algorithm was developed to first obtain the maximum number of successful transfer connections, and then minimize the total transfer waiting time. Wang et al. (2020) considered a train capacity-constraint, time-dependent passenger demand, and non-transfer passengers in railway timetable coordination optimization. A MIP model was proposed with the aim of minimizing the initial waiting time of passengers, the transfer waiting time and the transfer failure penalty. The model was linearized. For small-size problems, it can be solved using CPLEX. For large-scale size problems, GA and grey wolf optimizer were used to solve it. Case study results for the Shenyang rail transit network showed that the passenger transfer waiting time and the number of passengers failing to make transfers can be reduced by 26% and 9%, respectively. Yin et al. (2021) also considered train capacity, and time-dependent passenger demand in railway timetable coordination optimization. They developed a MILP model with the objective of minimizing the level of crowdedness at stations.

There are also some studies that use deterministic MP models to integrate the timetable coordination design and frequency setting, especially for the case of truck-feeder service integration design. Shrivastava and Dhingra (2002), Shrivastava et al. (2002), and Shrivastava and O'Mahony (2006) developed a deterministic MP model for train-feeder bus frequency setting and TCDPs. The optimization objective was to minimize the total system cost, which includes the transfer waiting time cost of users, and the operating cost of service providers. A GA was proposed to solve the mathematical model. The performances of the model and algorithm were demonstrated using several real-world case studies.

The review of using heuristic or meta-heuristic solution methods of deterministic MP approach to PT timetable coordination design is summarized in Table 5. All the studies formulated the problem as IP models using service offset times or vehicle departure times as decision variables. A few models are formulated as bi-objective or bi-level models. All the studies employed heuristic, or metaheuristic algorithms, such as GA, NSGA II, SA, TS, ACO, PSO (see Table 5), to solve the model. Most studies used real-world PT networks to test the effectiveness and efficiency of the proposed solution algorithms, while some studies considered the cases of trunk-feeder corridors. However, there is a lack of publicly available large-scale real-world benchmarking networks and related data for algorithm testing and comparisons to allow for a sound and systematic comparison of algorithms performance in terms of accuracy and scalability.

3.3.3. Heuristic or meta-heuristic solution methods for stochastic or uncertain mathematical programming models

Following the developments of deterministic MP models, stochastic and uncertain versions of MP models were also developed to capture the uncertainties in realistic PT transfer coordination settings. Désilets and Rousseau (1992) and Bookbinder and Désilets (1992) extended the deterministic model of Klemt and Stemme (1988) by considering the random arrival times of buses at transfer stations. Désilets and Rousseau (1992) developed two stochastic IP models. The first model minimizes the expectation value of transfer waiting times, while the second one minimizes the standard deviation of transfer waiting times. A local search heuristic algorithm with different searching strategies was developed to solve the model. The performance of the solution algorithm was verified by using a small transit network with 8 lines and 16 transfer stations. They concluded that the use of a fixed headway can achieve better transfer synchronization compared to using variable headways. The computational results showed that the waiting time required for transfer and initial trips can be reduced by 17%. Bookbinder and Désilets (1992) proposed to use a mean disutility function that could be the expectation of transfer waiting times, variance of transfer waiting times, or a critical threshold value, to better characterize the objective function of the PT transfer coordination problem. A simulation program was initially developed to address the stochastic bus travel times; then, an iterative improvement heuristic algorithm was designed to solve the model by changing the route offset times. Experimental results demonstrated some advantages of considering stochastic bus travel times compared to assuming deterministic ones. Teodorović and Lučić (2005) also extended the deterministic model of Klemt and Stemme (1988) by reformulating the objective function to consider the number of transfer passengers. The number of transferring passengers was assumed to be only approximately known and it was treated as a random number. A meta-heuristic algorithm based on the combination of an ant colony system and fuzzy logic was developed to solve the model. The results of numerical experiments demonstrated that the proposed fuzzy ant system had better performance compared to the ant colony system. Nair et al. (2013) proposed a two-stage stochastic programming model that treats the number of transfer passengers as a random variable. The model was solved by using a deterministic equivalent approach that specifies a set of deterministic scenarios.

Considering stochastic vehicle running time, Wu et al. (2015) developed a stochastic IP model with the aim of reducing the total transfer waiting time cost. The passengers at transfer stations were classified into three groups, i.e., transferring passengers, boarding passengers, and in-vehicle passengers. The model was solved by using a GA with local search. Wu et al. (2016) introduced the use of a safety control margin to address the stochastic disturbances in realistic settings of PT transfer coordination. A stochastic MIP model was developed using headways and slack times as decision variables. The model was solved using a B&B algorithm. Dou et al. (2016) also considered adding slack times at time control points along the route to improve schedule adherence as well as reducing transfer waiting times. The problem was formulated as a robust mixed-integer nonlinear programming (MINLP) model, which was linearized and solved by using Monte Carlo simulation combined with CPLEX. To address the impacts of uncertainty of transfer connections on the route choice of travelers, Gkiotsalitis et al. (2019) considered the variabilities of travel and dwell times in coordinated bus

timetabling. Instead of treating them as random variables with known probability distributions, they proposed to use time intervals to describe their variabilities resulting in a robust optimization problem. The timetable synchronization was modelled as a constraint. The objective function was to minimize the deviation of headways to keep good service regularity while maintaining transfer connections.

The reviewed stochastic MPs that use heuristic or meta-heuristic solution methods for the PT transfer coordination design are summarized in Table 6. The related models can generally be classified into two categories, namely stochastic models, and robust optimization models. Most models use offset times or departure times as decision variables, while some also consider slack times and headways. Vehicle running time, dwell time and passenger demand are usually treated as stochastic and uncertain variables in the formulated models. The models are solved by using various kinds of heuristic, meta-heuristic, or approximation algorithms.

3.4. Simulation approach

There are also some studies using simulation approaches, particularly using an agent-based simulation approach, to study the coordination of inter-modal or inter-route PT timetables. One of the advantages of using a simulation approach, compared to other approaches, is that it can implicitly represent the inter-dependencies and uncertainties in PT systems and their ramifications for timetable coordination design. In addition, it makes it possible to exam the performances of various alternative coordination schemes. Tsang et al. (2011) developed an agent negotiation model to coordinate the schedule of trains that belong to two different operating companies at a transfer station. Three different negotiation strategies were developed to increase the schedule coordination. The objective of the schedule coordination was defined as maximizing the revenue improvement. Li et al. (2011) also used an agent-based simulation model to coordinate the service between subway and bus systems. Passengers, buses, and subway trains were treated as intelligent agents who can negotiate with each other. The simulation model, using a day-to-day learning process, can dynamically model the route-choice behavior of passengers, which is very useful for predicting the passenger demand and flows in the network. The simulation results showed that the average waiting time of passengers can be reduced through better coordination of bus and subway systems. The same idea of using a multi-agent system for coordinating transfers was also studied by Elbaz et al. (2018). Focusing on stochastic passenger demand, Naumov (2020) studied the timetable coordination for a single transfer station using a simulation-based optimization approach combined with a GA.

3.5. Extended timetable coordination

Recently, the TCDP has been further extended in various ways, such as considering first or last train timetable coordination, integrated with vehicle scheduling, and incorporating passenger demand assignment. This section reviews these extended studies.

3.5.1. Timetable coordination for first or last trains

In the last 15 years, there has been a series of works focused on coordinating the first and last train timetables of railway networks. The timetable coordination of the first and last train is important because a well-coordinated timetable increases the accessibility for passengers, while a missed last-train connection makes passengers fail to reach their destination. Xu et al. (2008) extended the PT timetable coordination problem into the special cases of timetable coordination for first and last trains. With the aim of minimizing the total passenger transfer waiting time, a heuristic multi-layer coordination algorithm was proposed to generate the desirable departure

Table 6
Classification of heuristic or meta-heuristic solution methods of the stochastic or uncertain mathematical programming approach to the TCDP.

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Désilets and Rousseau (1992)	Min expectation and standard deviation of transfer waiting time	Offset time, headway	IP model	Simulation, local search heuristic algorithm	Small sector of the transit network in Montreal with 8 lines
Bookbinder and Désilets (1992)	Min mean disutility function	Offset time	IP model	Simulation, iterative improvement heuristic	Numerical network and network adapted from the Winnipeg network
Teodorović and Lučić (2005)	Min total transfer waiting time	Offset time	0–1 IP model	ACO and fuzzy logic	Hypothetical numerical example networks
Nair et al. (2013)	Min transfer waiting time	Offset time	Stochastic IP model	Deterministic equivalent	Rail and bus networks in Washington, D.C.
Wu et al. (2015)	Min total waiting time cost	Offset time, slack time	Stochastic IP model	GA with local search	Small numerical example network
Dou et al. (2016)	Min schedule deviation, transfer waiting time	Slack time	Robust mixed-integer nonlinear programming model	Branch-and-cut method, CPLEX	Network of three bus lines
Wu et al. (2019)	Min total system cost	Headway, slack time	Bi-level programming model	Heuristic algorithm, method of successive average	Small numerical example network
Gkiotsalitis et al. (2019)	Min headway deviation	Departure time	Minimax robust optimization model	Minimax approximation	Network of bus lines in the Hague

Table 7
Classification of timetable coordination for first or last trains.

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Xu et al. (2008)	Min total transfer waiting time	Departure time domains	IP model	Heuristic	First and last trains, subway network of four lines
Zhou et al. (2013)	Min waiting time, improving transfer connection reliability, and reducing number of passengers failed to making transfer	Departure times of the first or last train	MIP model	GA	First and last train coordination of the Guangzhou Metro network
Kang et al. (2015a)	Increasing the number of successful transfer connections	Departure time, dwelling time, running time	IP model	Genetic SA algorithm	Last train, small example network, Beijing subway network
Kang et al. (2015b)	Max connection headway	Departure time, dwelling time, running time, headway	IP model	GA	Last train, small example network, Beijing subway network
Kang and Zhu (2016)	Min total transfer waiting time	Departure time, dwelling time, running time, headway	IP model	SA	Last train, small example network, Beijing subway network
Li et al. (2016)	Max number of passengers with successful transfers	Departure time, headway	IP model	GA	Last train, Shanghai metro network
Kang et al. (2016)	Reducingmissed transfer connections, waiting time	Departure time, dwelling time, running time	IP model	CPLEX	First train, small example network, Beijing subway network
Guo et al. (2016)	Min cost-importance measures	Departure time	MIP model	CPLEX	First train, small example network, Beijing subway network
Kang and Meng (2017)	Min total transfer connection time	Departure time, number of trains	MILP model	Decomposition method, CPLEX	Last train, Beijing subway network
Dou and Guo (2017)	Min number of transfer failures	Departure time, dwell time, and running time	MINLP model	CPLEX	Last train, MRT network in Singapore
Yang et al. (2017)	Max number of successful transfers, Min last train running time	Departure time, running time	IP model	TS	Last train, Beijing subway network
Yang et al. (2018)	Max number of successful transfers, Min last train running time	Departure time, running time, platform delay	MINLP model	TS	Last train, Beijing subway network
Zhou et al. (2018)	Max number of passengers transferring successfully, coordinated directions, network accessibility	Departure/ arrival times	IP model	Hierarchical progressive algorithm	Last train, Guangzhou metro network
Ning et al. (2018)	Min transfer waiting time	Departure/ arrival times, dwell time, and running time	MIP model	CPLEX	First and last train, Beijing subway network
Guo et al. (2019)	Min total connection time	Departure/ arrival times	MIP model	GA	First train, Beijing subway network
Kang et al. (2019)	Max number of successful transfer passengers, Min transfer waiting time from rail to bus	Departure/ arrival times	MILP model	Decomposition method, and CPLEX	Last train, Vienna city's subway network
Yin et al. (2019)	Max social service efficiency, Min revenue loss	Departure time, dwell time	Bi-level programming model	GA, active set	Last train, numerical testing network, Beijing subway network
Li et al. (2019a)	Max the number of passengers making successful transfer	Departure/ arrival times	IP model	GA	Last train, Shenzhen metro network
Chen et al. (2019a)	Max number of successful transfers, Mix extra dwell time	Departure/ arrival times, running time, dwell time	IP model	Brach and cut algorithm	Last train, Shenzhen metro network
Chen et al. (2019b)	Max weighted sum of accessible OD pairs	Departure/ arrival times, running time, dwell time	MIP model	GA	Last train, Shenzhen metro network
Zhou et al. (2019)	Max number of passengers successfully reaching destinations	Departure/ arrival times, passenger assignment	MILP model	CPLEX	Last train, numerical testing network, Beijing subway network

(*continued on next page*)

Table 7 (*continued*)

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Yu et al. (2019)	Min number of passengers failed to transfer, Min schedule changes	Departure times, extra dwell time	IP model	CPLEX	Last train, Beijing subway network
Li et al. (2019)	Min total waiting cost	Departure times, dwell time, running time, transfer passenger flow	IP model	GA	First Train, subnetwork of Beijing subway network
Li et al. (2020)	Max total time satisfaction	Departure times, dwell time, running time, headway, transfer passenger flow	IP model	Artificial bee colony algorithm	First Train, Shanghai urban rail network
Guo et al. (2020)	Max number of synchronization events, min biggest departure time difference	Departure/ arrival times, dwell time, running time	MIP model	NSGA II	Last train, Beijing subway network
Yang et al. (2020)	Min number of inaccessible time-dependent demand pair, Min number of transfer-failure passengers	Matching between time-apace arcs and passenger trajectories, last-train trajectories	0–1 ILP model	Lagrangian relaxation, sub-gradient algorithm	Last train, numerical testing network, Beijing subway network
Yang et al. (2021)	Max number of passengers having successful transfers	Departure/ arrival times, dwell time, running time	Chance constraint programming model	CPLEX, TS, local search	Last train, Nanjing and Beijing subway networks
Kang et al. (2021)	Min total passenger transfer waiting time	Departure time of first trains, bus departure time and headway	MIP model	Sequential solution approach, CPLEX	First train and bridging bus in Beijing
Huang et al. (2021)	Max number of successful transfers, number of valid coordination with connecting modes, coordination quantity for all modes	Departure/ arrival times, running time	MIP model	Commercial solver	Last train, urban rail transit network in Beijing
Zhang et al. (2021)	Max number of feasible transfers	Departure times of last trains at the starting stations	IP model	Double-temperature SA algorithm	Last train, numerical example with four lines

time domains for first and last trains. Zhou et al. (2013) developed MIP models for coordinating timetables of both first and last trains. For first-train timetable coordination, the defined objective was to minimize passenger waiting times, including waiting times at a boarding station and transfer stations. For last-train timetable coordination, except for minimizing passenger waiting time, other two objectives, namely minimizing the number of passengers who failed to reach their destinations, and improving transfer the connection reliability, were also considered in the formulated model. A GA was proposed to solve the two models in an acceptable computation time. The model and solution algorithm were tested on a network adapted from the Guangzhou metro network. Ning et al. (2018) defined a transfer train index for the purpose of calculating the transfer waiting time. In addition, the last connection train index and the first connection train index were defined to identify failed transfers and successful transfers.

Because of the importance of the last train transfer to passengers for reaching their destinations, there is an increasing research focus on last train timetable coordination. Kang et al. (2015a) proposed an IP model that was adapted from the Markowitz mean–variance model to increase the number of successful last train transfer connections in a railway network. The concept of a transfer binary variable, which is similar to the binary synchronization variable used in Ceder et al. (2001) and Ibarra-Rojas and Rios-Solis (2012), was defined to quantify the number of successful transfer connections. A genetic simulated annealing algorithm was proposed to solve the model. Kang et al. (2015b) further considered the maximization of the connection headway for transferring passengers for the last train timetable coordination. A GA was used to solve the formulated IP model. To solve large-scale size problems, Kang and Meng (2017) further developed a two-phase method to decompose the original MILP model into two small-size MILP modes that were solved by using commercial optimization solvers. Kang et al. (2019) further considered the coordination of last-train and bridging bus service. With the aim of maximizing the number of successful transfers and at the same time reducing the transfer waiting time from the last train to bridging buses, a MILP model was developed. The model was first decomposed into sub-problems, and then each sub-problem was solved using CPLEX. Zhang et al. (2021) recently proposed to incorporate the spatial rationality of passenger transfer processes, from the aspects of transfer angle and transfer distance, into the last-train timetable coordination optimization. Computation results of numerical experiments show that the number of feasible last-train transfers can be increased by 67% using a double-temperature SA algorithm. In addition, more practical last-train transfers can be realized after including the spatial rationality principle.

Using automated fare collection (AFC) system data, Li et al. (2016) developed a model to maximize the number of passengers who can successfully make the last-train transfer to reach their destinations. The model was solved using a GA. Li et al. (2019a) further emphasized the importance of including the actual transfer passenger flow in the last train transfer coordination optimization. They proposed to estimate last-train transfer passenger flow data from historical smart card data. Dou and Guo (2017) proposed to minimize

the number of transfer connection failures in the last train timetable coordination. Zhou et al. (2018) proposed a hierarchical progressive algorithm for coordinating last train schedules. The objective was to maximize the number of passengers transferring successfully, the number of coordinated route directions and the network accessibility.

There is a group of studies reformulating the last train timetable coordination model as a bi-objective or a bi-level model. For example, except for reducing the number of passengers who failed to transfer, Yu et al. (2019) proposed a second objective of minimizing the timetable changes, compared to the actual timetable. Considering the interests of government agencies and train operating companies, Yin et al. (2019) proposed a bi-level optimization model for coordinating last-train transfers. The upper level, taking the perspective of government agencies, maximized the social service efficiency; while the lower level, taking the perspective of operating companies, minimized the revenue losses. The model was solved using a GA combined with an active-set approach. Except for maximizing the number of synchronization events, Guo et al. (2020) recently considered also minimizing the longest transfer synchronization time in the last train timetable coordination, which is similar to the objective function specified in Wu et al. (2015).

There is also a distinctive set of studies considering the coordination of first-train timetables. Kang and Zhu (2016) developed an IP model with the objective of minimizing the total passenger transfer waiting time. The model was solved using a SA algorithm. The other first-train timetable coordination model that aimed to minimize the number of missed transfer connections and passenger transfer waiting times was solved using CPLEX (Kang et al., 2016). Guo et al. (2016) developed another first train timetable coordination model using train departure times as decision variables. The objective was to minimize a cost-importance measure that considers the importance of lines, stations, and transfer costs. The model was solved using CPLEX. Guo et al. (2019) further considered the coordination of the first-train timetable and the transfer between first train and bus services. A MIP model was developed with the objective of minimizing the total connection time. The model was solved using a GA. Li et al. (2019) and Li et al. (2020) emphasized the importance of the cost function in first train timetable optimization. Instead of simply minimizing the total transfer waiting time, they proposed to add a buffer time, which can be obtained by conducting a stated preference survey of passengers, to reduce the perceived risk of transfer passengers and increase the number of comfortable transfers. Recently, based on the previous first train timetabling model, Kang et al. (2021) further developed a bus bridging service model under bridging bus fleet size constraint. The integrated optimization of bus bridging and first train timetabling can help in further reducing the total passenger waiting time. However, it was computationally intractable to solve the integrated optimization model. Thus, a sequential solution approach, together with the use of CPLEX, was proposed to solve the model. Computation results from both numerical example network and the Beijing subway network demonstrated the effectiveness and efficiency of the proposed optimization model and solution approach.

The reviewed studies on first and last train timetable coordination are summarized in Table 7. It is evident that it is an upcoming research topic with an increasing number of studies since 2015. There are more studies on last train timetable coordination than on first train timetable coordination. This can be explained because of the importance of last train connections, compared to first train connections since it is the last chance for passengers to reach to their destinations. Most studies formulated the problem as linear IP models or nonlinear IP models that can be linearized so that they can be solved by using optimization solvers. However, most studies solve the model using meta-heuristic algorithms, such as GA, TS, and SA, to get good solutions within an acceptable computation time for large-scale real-world problems. Recent studies on first and last train timetable coordination are mainly focused on maximizing the network accessibility, reachability, and transferability (e.g., Chen et al., 2019a, 2019b; Zhou et al., 2019; Yang et al., 2020), addressing the uncertainty in transfer passenger flow (Yang et al., 2017, 2018; Yang et al., 2021), and coordinating with other connecting modes, such as intercity railway and air transport (Huang et al., 2021) and bridging bus (Kang et al., 2021).

3.5.2. Timetable coordination integrated with vehicle scheduling

Traditionally timetable coordination design and vehicle scheduling are performed separately and in a sequential manner, with the output of the former being the input of the latter. Recently, there is an increasing number of studies that aim at integrating these two activities and solve them simultaneously. Guihaire and Hao (2010) proposed to simultaneously optimize transit timetabling and vehicle assignment with the objectives of (i) maximizing the quantity and quality of transfer opportunities, (ii) improving headway evenness, (iii) minimizing fleet size, (iv) minimizing the length of vehicle deadheads. These four objectives were combined into an aggregated weighted function. A nonlinear waiting time cost function was used in the optimization model to generate transfers with close-to-ideal waiting times. The optimization model was solved by using an iterated local search metaheuristics combined with an exact linear quasi-assignment algorithm. Computation results on a real transit network from the area of Orléans, France demonstrated that the simultaneous timetabling and vehicle assignment can achieve better improvements in both quality of service and resources utilization compared to existing and sequential solution approaches. Petersen et al. (2013) developed an IP model to integrate the timetable synchronization design and vehicle scheduling of a bi-modal train-bus network, with the objective of minimizing passenger transfer waiting time and vehicle operating cost. The decision variables were the offset times of bus routes. A large neighborhood search heuristic algorithm was developed to solve the model. Computation results showed that the passenger transfer waiting time can be significantly reduced while maintaining the vehicle operating cost. Ibarra-Rojas et al. (2014) proposed a bi-objective IP model for the integrated timetable coordination and vehicle scheduling problem. An ε -constraint multi-objective optimization method was used to solve the bi-objective optimization model to examine the trade-off between maximizing the number of transfer passengers benefited from the coordinated timetable and reducing the total vehicle operating cost. Liu et al. (2017) also developed a bi-objective IP model with the objectives of maximizing the number of simultaneous vehicle arrivals at transfer stops and minimizing the fleet size. A deficit function-based heuristic combined optimization algorithm was developed to solve the model. Its effectiveness was illustrated using numerical examples. Fonseca et al. (2018) proposed a metaheuristic approach for integrating timetable coordination and vehicle scheduling with the aim of minimizing both passenger transfer and vehicle operating costs. A MIP model was formulated by considering the addition of extra vehicle dwell time as well as departure times. Ataeian et al. (2021) also developed a bi-objective

Table 8
Classification of integrating timetable coordination and vehicle scheduling.

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Guihaire and Hao (2010)	Min fleet size and length of deadheads, Max quantity and quality of transfer opportunities, and headway evenness	Offset time and vehicle assignment	Multi-objective optimization model	Heuristic solution method, iterated local search metaheuristics combined with an exact linear quasi-assignment algorithm	Real transit network of Orléans, France
Petersen et al. (2013)	Min waiting time, total cost	Offset time	IP model	Large neighborhood search heuristic	Train-bus network in Copenhagen
Ibarra-Rojas et al. (2014)	Max number of transfer passengers, min vehicle operating cost	Departure times of vehicles	Bi-objective IP model	ε -constraint method	Networks with one or five transfer stations
Liu et al. (2017)	Max number of simultaneous arrivals of vehicles, Min fleet size	Offset time	Bi-objective IP model	Heuristic algorithm	Numerical testing network
Fonseca et al. (2018)	Min transfer and operational costs	Departure times, Dwell time	MIP model	Matheuristic	Train-bus network in Copenhagen
Ataeian et al. (2021)	Max number of synchronized arrivals, Min fleet size	Offset time, headway, number of vehicle departures	MINLP model	NSGA II, GAMS	BRT networks in Tehran

optimization model for coordinating timetables of bus rapid transit (BRT) networks. The first objective is to maximize the total number of synchronized vehicle arrivals at transfer stops. The second objective is to minimize the fleet size required. Weighting factors were employed to transform the two objectives into one objective. For a small size problem, it was solved using optimization solver GAMS, while for a large-scale problem, it was solved by using NSGA II.

Table 8 summarizes the studies on integrating the timetable coordination design and vehicle scheduling problems. It shows that all the studies formulated the combined problem with the use of IP models that are solved mainly using heuristic or metaheuristic methods. All the studies considered minimizing the fleet size or operating cost in the optimization objective.

3.5.3. Timetable coordination incorporating passenger demand assignment

Making changes to timetables may have an impact on the route/trip choice behavior of passengers, which in turn impacts the design of timetables. Thus, there are some studies integrating passenger demand assignment into the timetable coordination design. Parbo et al. (2014) proposed a bi-level optimization framework that treats passenger route choice as the lower-level problem, and timetable coordination design as the upper-level problem. A heuristic solution method was used to address the bi-level optimization problem. Case study results of the Denmark PT network showed that the solution method can achieve a significant reduction of passenger transfer waiting time compared to the existing timetable. Liu and Ceder (2018) also proposed to use a bi-level optimization model to optimize the route headway and offset times. They solved the model by using a deficit function optimization technique and commercial optimization solvers. Ibarra-Rojas et al. (2019) studied the joint optimization of frequency setting, departure time setting, headway determination, and passenger assignment in the development of a synchronized timetable. A mixed-integer optimization model was developed with the objective of minimizing both the operator and passenger costs. The model was solved by using an iterative heuristic algorithm. Chu et al. (2019) also considered the assignment of passengers to different travel paths. They first enumerated all the feasible paths for all OD pairs. Then, the original timetable coordination model was reformulated as a set partitioning problem that has less computation complexity and can generate a much tighter lower bound. Wu et al. (2019) proposed a bi-level model for transfer coordination. The upper level is a schedule coordination model with the objective of minimizing total system costs; the lower level is a passenger assignment problem considering the rerouting behavior of passengers. The model was solved using a heuristic iterative algorithm incorporating the method of successive averages.

Table 9 summarizes the related studies of incorporating passenger demand assignment into timetable coordination design. It shows that all the studies are focused on the problem setting of a network. A bi-level programming model is mostly used as the modelling and optimization framework. A vehicle capacity constraint, limiting the on-board passenger load, is usually considered in the model formulation. The models are all solved using heuristic algorithms. There is a lack of exact solution methods for solving the bi-level models. In addition, the route/trip choice behavior involves several assumptions that may not hold in practice. However, with the availability of smart card data, the route/trip choice models may be calibrated to better describe the route/trip choice behavior of passengers.

One interesting observation from the above review of the three extensions of the TCDP is that almost all the extended TCDPs are solved using the mathematical programming approach. The other three solution approaches are seldom applied to solve the extended TCDPs. Thus, one promising future research direction will be exploring other solution approaches or a combination of different solution approaches to solve the extended TCDPs, and compare the performances of different solution approaches.

An analysis of the review results summarized in Tables 1–9 shows that for the objective functions, 39% of the reviewed studies maximize the number of successful transfer connections or simultaneous arrivals of vehicles, 36% minimize transfer waiting time, and 20% minimize the total system cost. A multi-objective optimization approach may be required to explore the trade-off among different

Table 9
Classification of integrating timetable coordination and passenger demand assignment.

Authors (year)	Objective	Decision variable	Model characteristic	Solution method	Problem setting
Parbo et al. (2014)	Min transfer waiting time	Offset times	Bilevel optimization	Heuristic algorithm	Transit network in Denmark
Liu and Ceder (2018)	Min operator and passenger costs	Offset times, headway	Bi-level programming model	Deficit function technique, optimization solvers	Small numerical example network
Ibarra-Rojas et al. (2019)	Min total system cost	Departure time, holding time, headway, number of passengers	Nonlinear mixed integer programming model	Heuristic algorithm	Transit network in Santiago, Chile
Chu et al. (2019)	Min total travel time of passengers	Departure time, running time, headway, passenger demand	MILP model	Heuristic algorithm	Small testing and Mandl's networks
Wu et al. (2019)	Min total system cost	Headway, slack time	Bi-level programming model	Heuristic iterative algorithm	Small numerical example networks

objectives. As for the decision variables, offset time or vehicle departure time are the most common decision variables, used in 81% studies, while headway, dwell time, and slack time, are used in 29%, 17%, and 10% of the reviewed studies, respectively. A survey amongst different PT operators, may be conducted to understand the most preferred decision variables. Finally, 78% of the reviewed studies use a mathematical programming approach to solve the TCDP problem. A combination of different solution approaches deserves further explorations.

4. Future research agenda and directions

As evident from our synthesis of the literature, the TCDP has received increasing research interest in the last decade. This interest has been stimulated by an increased focus on user experience where transfers play a major role as opposed to merely focusing on vehicle arrival reliability as well as the increasing availability of data and modelling techniques that enable specifying and solving more extensive variants of the TCDP. Through the comprehensive literature review, we have identified six promising directions for future research, which are elaborated in the subsequent subsections. These future research directions pertain to emerging trends observed in the literature, triggered by technological and modelling advancement, computational capabilities and/or planning agendas.

4.1. Integrating with other PT operations planning activities

As mentioned above, the TCDP is solved in the tactical planning phase, as part of the timetable design. Whereas PT planning problems have been traditionally solved in isolation, advances in solution techniques and computational capabilities facilitate the joint consideration of several planning problems. Heuristic and exact approaches have been proposed for solving the timetabling problem with either vehicle scheduling - a subsequent problem in the conventional PT planning process - and/or line planning – a preceding problem in the conventional PT planning process (Michaelis and Schöbel 2009, Kapsi and Raviv 2013, Schöbel 2017, Carosi et al., 2019). As evident from the review in Section 3.5.2., there is by now a considerable body of literature extending the TCDP so that it is solved simultaneously with the scheduling of the respective rolling stock. However, there is limited knowledge on how planning for optimal transfer coordination affects network design and frequency setting. Furthermore, driver scheduling costs and constraints may impact the ability to implement a transfer coordination plan and the associated vehicle scheduling. Future research may thus incorporate network design, frequency setting, and crew scheduling and rostering considerations into the TCDP instead of solving those iteratively or selecting sub-optimal solutions.

4.2. Incorporating passenger choice behavior

The integration of TCDP with subsequent planning steps involves the allocation and circulation of resources – vehicles and crew. In contrast, the integration of TCDP with line planning makes it crucial to consider the consequences for passenger flow distribution. Moreover, even when line planning is considered pre-determined, various solutions of the TCDP may result in passengers' choosing different itineraries or even different transfer locations or line combinations altogether. As shown in subsection 3.5.3, several studies have proposed incorporating passenger assignment into the TCDP, all of which in the form of heuristics. This development, especially in the last three years, is part of an increasing research focus on passenger-oriented train-scheduling models as part of an industry's shift towards planning and measuring services from passengers' experience which is currently underway yet much remains to be done to adequately capture passengers' perspective (Parbo et al., 2016). To capture the impacts of alternative timetable coordination solutions on the resulting passenger flows, it is essential to represent temporal variations in service provision and passenger flow distribution across service trips. Unlike frequency-based transit assignment models, schedule-based transit assignment models adopt a time–space graph representation, explicitly accounting for individual transit vehicle runs and thus allow attaining passenger flows at the individual vehicle trip-segment level (Gentile et al., 2016). Schedule-based transit assignment models can be embedded as part of TCDP solution procedure with improvements in computational power and their increasingly availability in commercial software packages. However, traditionally scheduling tools (e.g., HASTUS and Trapeze) and transport network and demand forecasting tools (e.

g., VISUM, EMME, and TransCAD) are developed and applied separately, limiting the ability to apply transit assignment models as part of the timetable design process. Future research may enrich the behavioral representation of passenger choices in the context of transfer coordination by considering passenger preferences in relation to alternative transfer locations and attributes, risk minimization considerations and traveler heterogeneity.

4.3. Using multi-objective optimization

The analysis of the results from Tables 1–9 shows that a variety of objective functions have been considered in previous studies. Future studies may investigate the formulation of a multi-objective optimization based to allow for the identification of Pareto optimal solutions from users', operators', and community's perspectives. In addition, more effective and efficient solution methods and algorithms for multi-objective optimization models should be developed.

4.4. Utilizing PT big data to support decision making

Advancements in AFC systems, passenger flow analytics and smartphone travel app services, introduce new opportunities for developing techniques for improving overall passenger journey reliability. The availability of historical passenger flow big data enables the selection of services for which transfer coordination needs to be prioritized (Yap et al., 2019). Depending on the local data ownership conditions, it may not be possible to identify and measure transfers between different PT operators. One-stop-shop travel apps may circumvent this problem by collecting individual information across operators. Moreover, the availability of information on passenger journeys can facilitate the coordination of feeder and collector lines (Gkiotsalitis 2021). Another important avenue paved by the deployment of AFC, i.e., smart card data, involves the more nuanced and precise estimates of the impact of various transfer locations and attributes (Guo and Wilson 2011; Hänseler et al., 2020; Nielsen et al., 2021), crowding levels (Hörcher et al., 2017; Yap et al., 2018), and denied boarding (Yap and Cats 2021) on passenger flow distribution. These estimates, if integrated into the TCDP, can better assess alternative solutions by considering their consequences for passenger choices and quantifying the related societal costs induced by changes in crowding levels, transfer conditions and missed connections.

4.5. Employing more flexible vehicle deployment and scheduling

Advancements in vehicle automation technology are expected to have pronounced impacts on PT service provision. A related development is the possibility of deploying automated modular vehicles that will allow for a more flexible allocation of service capacity and the dimensioning of service fleet (Chen et al., 2020; Liu and Ceder, 2020; Zhang et al., 2020; Pei et al., 2021). It is a challenging and interesting research topic to solve the TCDP for an automated modular vehicle-based PT system. It requires considering variable vehicle capacity and passenger-to-vehicle assignment in formulating and solving the TCDP (Gong et al., 2021). In addition, various transfer coordination scenarios, such as horizontal, vertical, and possibly diagonal coordination and coupling of moving automated modular vehicles, deserve further explorations (Ceder, 2021). The deployment of self-driving vehicles will also result in changes to line planning and frequency setting (Hatzenbuhler et al., 2021), with service lines widely expected to be operated with larger fleets of lower capacity vehicles. Such changes will have significant implications for the coordination of transfers between services. Furthermore, the possible integration of passenger and freight distribution services (Bruzzone et al., 2021) may call for the development of new variants of the TCDP which allow for the consolidation of passenger and goods flows at selected interchange locations while considering the capacity constraints for both types as part of a multi-commodity problem formulation. Finally, a more flexible provisioning of feeder and collector services at interchange hubs facilitated by the deployment of on-demand mobility systems will reduce the need to coordinate transfers at the tactical planning phase and will shift those into the real-time management domain.

4.6. Developing benchmark cases

The review of the literature has also made it evident that there is a plethora of variants of TCDP formulations and its related properties, objective function compositions and specifications, performance metrics, constraints considered and corresponding solution algorithms. The absence of common benchmark networks and algorithms hinders the systematic analysis and comparison of the performance and transferability of the proposed modelling and solution approaches. Benchmark cases have been highly instrumental in the assessment and development of vehicle routing and traffic assignment algorithms. We hope that a scientific conduct embracing open-data and open-code will facilitate such developments also in the TCDP domain.

5. Conclusions

For public transport (PT) to be attractive, it is essential for transfers to be coordinated and optimized to provide travelers with well-connected, synchronized, and accessible seamless door-to-door service. Well-coordinated transfers can attain many benefits for PT users, operators, and authorities, such as reducing missed transfer connections and reducing long transfer waiting times as well as under some circumstances potentially reducing operation costs and improving PT patronage.

In this paper, we systematically reviewed and synthesized the relevant studies on the PT transfer coordination design problem (TCDP) as well as three common extended topics of the TCDP, namely first or last train timetable coordination, integrated with vehicle scheduling, and incorporating passenger demand assignment. The review is focused on the solution approaches to the TCDP. We

classified the identified four solution approaches, namely heuristic rule-based approach, analytical modelling approach, mathematical programming approach, and simulation approach. Furthermore, we conducted a detailed analysis of each solution approach in terms of optimization objectives, decision variables, solution methods, and problem settings, as well as model characteristics for the mathematical programming approach and three common extended topics of the TCDP.

The first observation from the literature review is that the study of TCDP has led to an increasing number of publications, especially for the extended topic of first or last train transfer coordination optimization. This is presumably the result of a more network-wide approach for service planning in urban rail services, as well as advancements in computing technologies. The second observation is that the mathematical programming (MP) approach is the most widely adopted solution approach to the TCDP and its extensions. Compared to other solution approaches, the MP solution approach is more efficient by utilizing high-performance computing techniques. Heuristic and meta-heuristic algorithms are the most popular solution methods for MP models. Third, there is a lack of publicly available large-scale real-world benchmarking PT networks and related data to allow for a sound and systematic comparison of algorithms performances in terms of their accuracy and scalability. Open benchmarking networks and databases should be established for stimulating more comparative studies. Leveraging on open benchmarking networks and databases, different performance metrics and indicators of computational efforts should be compared, which can help decision-makers in selecting among the alternative approaches for solving the TCDP. Finally, except for computational results from academic research, the implementation results of solution methods for large-scale real-world PT networks should also be reported from the PT practitioner side, including evaluations of field implementations and the resolution of practical considerations.

In this review, we identified six promising research directions for setting future research agenda. Further developments in these research directions require novel problem formulations, advancements in modelling and efficient solution methods, and thereby can help achieve the vision of 'seamless travel' in the next two decades. The advancements of big data analytics and computing technologies may provide more effective and efficient solution methods to the TCDP and increasing impacts on practical implementations.

Declaration of Competing Interest

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

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