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Public transport for smart cities: Recent innovations and future challenges

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ABSTRACT

The idea of a smart city is one that utilises Internet-of-Things (IoT) technologies and data analytics to optimise the efficiency of city operations and services, so as to provide a high quality of life for its citizens. Due to reduced public funding, many public transport systems are already facing challenges to maintain their services. For a smart city, the goal of public transport is not simply the movement of people, but the provision and enhancement of mobility for living. This will be particularly challenging due to changes in habitation trends and work patterns. For example, the growth of mega-cities has led to extreme traffic congestion in city centres and urban sprawl on their outskirts. In order to provide sufficient coverage and frequency of service, an integrated co-ordinated multi-modal public transport system is needed, leading to substantial increase in operational complexity. Environmental concerns and the recent pandemic may also change work and commuting patterns in the future, with more people working from home and companies adopting flexible work shifts. For smart cities, public transport must offer ubiquitous access, real-time response to demand, convenience and quality service, and energy-efficient operations. This paper will discuss the challenges in network design, operations planning, scheduling and management of smart public transport systems. A brief survey of recent research and innovations will also be presented.

1. Introduction

This paper discusses the challenges of designing and operating public transport systems today. On the one hand, the trend of urbanisation and increased consumer expectations have increased the scale and scope of the services expected. On the other hand, the budget for these systems are often insufficient to support the improvements needed to operate the increasingly complex public transport systems. Recently, many cities have launched “Smart City” initiatives to explore and exploit advanced computer and communications technologies and big data analytics to improve the efficiency of its operations and services, in order to provide a high quality of life for its citizens. How can the advances in IoT (Internet of Things) technologies help in designing and operating public transport systems? In this paper, we summarise the performance goals for public transport for smart cities, and mention some recent innovations. We also provide a brief survey of recent research. Finally, we discuss how changes in habitation and work trends might impact public transport systems in the future.

The world has become increasingly urbanised. There are around 8 billion people in the world with more than half living in urban areas. More than that, of the 55% of the world’s population that live in urban areas, 7% live in what are called mega-cities. The United Nations defines a mega-city as one with more than 10 million people. There are now 33 mega-cities in the world and it is expected that there will be 43 mega-cities by 2030, in ten years’ time. Interestingly, 6 of the 33 mega-cities in the world are in China. In fact, the cities in China are growing so big that they are merging into one another. In China, we now talk about not just mega-cities but city-clusters (Xin, 2021). In south China, the cluster of cities around the Pearl River Delta have re-branded themselves as the Greater Bay Area, which includes 9 municipalities in Guangdong province (the two biggest being Guangzhou and Shenzhen) plus Hong Kong and Macao, and covers an area of 55 thousand sq. km. with over 70 million population! China’s target for its city clusters is the provision of a “one-hour quality living circle”, meaning that citizens can engage in both recreational and economic/employment activities without spending more than an

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hour travelling to and fro. If we are to be able to travel within the city-cluster within one hour, then the provision of good public transport is a major prerequisite.

2. Performance Goals for Smart Public Transport

Focussing on public transport, what are the performance criteria that we want for the public transport system for a smart mega-city? We posit that there are five essential performance goals, summarised by the acronym *S-M-A-R-T*.

2.1. S for Service

Firstly, a smart city must ensure that public transport has good coverage, that service is available in all parts of the city, so that the system can reach people in the residential areas and commercial areas. People should be able to use public transport to get to where they want to go, and the service frequencies are sufficient to support the activities for their daily living. An indicator of the quality of service for a public transport system may be the average commuting time. A secondary concern is affordability; the pricing of the various transport services should not prejudice the economically disadvantaged.

2.2. M for Mobility

By mobility, we mean that people can get to where they want to go quickly and smoothly. Within the one-hour quality living circle of a mega-city, one should be able to get from one place to another in the city using relatively direct routes without too many interchanges. When the trip involves different segments, passengers expect a smooth transfer between different trains/buses or even different modes. Indicators of good mobility may be the number of transfers required and the additional journey time compared to a direct door-to-door trip. This means that the public transport system must have enough capacity and run efficiently in order to support all the trips required by all the people.

2.3. A for Accessibility

A third aspect is ease of access. In addition to getting people to their destinations quickly, we need it to be easy for people to get onto the public transport system, and the journey is comfortable while they are travelling on the public transport system. An indicator of the accessibility of the public transport system may be the distance from the origin of the trip to the access point of the public transport and the distance from the alighting point to the destination.

The above three goals refer to the design and planning of the public transport system.

2.4. R for Responsiveness

However, we know that demand is stochastic and not deterministic; people change their minds and things never go to plan. Therefore, another key goal for a public transport system must be responsiveness. It should have flexibility to handle changes in demand real-time or any disruptions that might occur.

2.5. T for Technology

For a public transport system to be smart, it must take advantage of the technologies available. This means not just exploiting the latest rail and vehicular technologies, but also communication technologies, so that it can provide better information for passengers, thereby enhancing their travel experience and improving the service quality provided.

At this point, the reader might be thinking: the word SMART might be a good acronym for the five main goals for smart public transport systems for mega-cities; but aren't these also the targets for *any* public transport system, smart or not? So what makes this smart? So what is different? Our response is the following. While the five goals represented by SMART are the same for any public transport system, recent advances in technology have allowed us to explore new innovations and new solutions. Our goals might be the same, but because of advances in technology, because of big data, analytics, improvements in computation and advances in communications technologies, we might be able to provide new solutions that can better achieve these 5 goals. Along the way, because of generating new solutions, we might have new problems.

There is no universally agreed-upon definition of a smart city, but almost all references include the following three aspects: use of communications and Internet-of-Things technologies, data analytics for better decision-making and more efficient operations, and the objective of improving social welfare and the quality of life for the citizens. Many Smart-City initiatives involve improved or new modes of transport services. Door-to-door individual transport has been transformed by companies, such as Uber and Lyft, whose innovative operational mode uses information technologies to better match customers with the freelance drivers. Unlike traditional taxis, there is no need for the vehicles to roam the city streets looking for potential customers, thus reducing fuel costs and pollution. Likewise, public transport services can exploit information technologies to offer more flexible and customized services. For example, in a smart city, passengers boarding a bus can indicate their alighting stops. When the bus is full, the driver may skip the next stops and take a shortcut to the next alighting stop. This provides better service to on-board passengers, but creates more complexities for planning and operations. How to take care of customers waiting at the skipped stops? How to manage the schedule and roster when buses overtake and arrive early at the depots? New types of services may require new planning models. Overall, we may need to change our planning approach from the old "just-in-case" mindset when data was not available, to a "right-on-time" mindset when data is ubiquitous in a smart city.

In the following sections, we will investigate these five goals in turn and mention some of the changes that may be needed because of the smart technologies that we now have. We will also provide a brief survey of recent research and highlight some examples.

3. Service

The goal of "Service" for a public transport system is the provision of affordable means of travel in support of the activities for all the people. With government spending on public transport exceeding 2% of GDP in many countries, the cost-effectiveness of the provision of public transport is a major concern.

Construction of public transport infrastructure (e.g. building an underground rail system, bus depots) involves huge capital investments. However, as noted by Borndörfer, et al. (2010), these major decisions were often heavily influenced by politics and taken based on evaluation of a few scenarios using aggregated macro-economic data. Investment costs for different transport modes vary dramatically. The construction cost for urban rail or metro system is well over US $75 million per kilometre, that for tram/streetcars around US25 m per km, while bus rapid transit systems may cost only US$2 m per km. Therefore, (underground) metro lines may be justified only for travel corridors with large ridership. Of course, different transport modes also have varying degree of environmental and economic impact. What is needed is a holistic view of systems planning of public transport across all modes. In the future of Big Data, it would be much easier to obtain fine-grain information about travel behaviour, so systems can be designed that better match the needs of the people. There has been little research on integrated infrastructure planning and design for multi-modal public transport network; this is an important direction for future research.

The study of service provision heavily relies on travellers' data. The mainstream research areas include data pre-processing, passenger behaviour modelling, and planning/operational optimisation. Data pre-processing derives the Origin-Destination matrices and passengers' spatial-temporal distribution, which are essential to other planning stages and research applications. In the past, obtaining data (e.g. via surveys) was very costly. Nowadays, passengers' data can be obtained through smart card data or mobile phones. Heterogeneous data sources and anomalies are the main difficulties (Liu and Zhou, 2019, Bagchi et al., 2005). We will further discuss the evolution of data for public transport service planning in Section 7.

3.1. Public Transport Service Planning Models and Methods

In courses on transportation planning, one is taught that the process involves four stages — firstly the network design and line planning; secondly service timetabling, then vehicle scheduling, and finally crew rostering. The four stages in the planning process are done sequentially, because the whole problem is just too big to think about all at once. That this sequential process may lead to sub-optimal solutions has been well-noted by practitioners and researchers, e.g. Bussieck, Winter and Zimmermann (1997). Moreover, the models used in each of the planning stages are mostly deterministic and use historical data as inputs. Below, we summarize the models and methods for these four stages, and mention some recent work on integrated planning.

Line planning is the problem of determining the set of service routes (lines) and their frequencies. The somewhat conflicting objectives are operational cost minimisation and maximisation of customer service quality (often with sojourn time as a surrogate measure). Early work on this problem determined the routes and frequencies sequentially. For the town of Wallasey in England, Lampkin and Saalmans (1967) generated routes using a path-building heuristic and then determine frequencies by random search, subject to a constraint on the bus fleet size. Their problem has 81 buses and a dozen lines. Dubois, et al. (1979) developed a similar 2-step heuristic for the bus system in Toulouse with about 50 routes. Later, van Nes, et al. (1988) developed a Lagrangean-based additive procedure to jointly determine the routes and frequencies, tested with data from Groningen with a few routes but several thousand trips per day. By the 1990's, exact solution methods using nonlinear or mixed-integer optimisation models were in use, either with cost minimisation as the objective and service quality as constraints, or vice versa. See, for example, Schöbel (2012), and the work on railway systems by Bussieck, et al. (1996) and Claessens, et al. (1998).

Given lines and frequencies, the next planning stage is timetabling, the setting of despatch times of the buses/trains from the termini and targeted arrival times for the stations en-route. Newell (1971) considered a single line (with no capacity constraints) and derived analytically that total waiting time is minimised when the despatch headway is inversely proportional to the square-root of the arrival rate of passengers. Ceder (1986) presented a comprehensive method for bus timetabling that allowed uneven headways for balanced loading of the buses, tested on a heavy bus line in Los Angeles. An early study on rail timetabling is by Salzborn (1969) who used dynamic programming to schedule a suburban rail line with skipped stops. Serafini and Ukovich (1989) introduced the Periodic Event Scheduling Problem for computing periodic timetables with hundreds of events. Mixed integer programming models were also developed for aperiodic timetables. Optimisation models for timetabling are currently in use in many large-scale rail systems, such as the Dutch Rail Network, the Berlin Underground and BLS-Switzerland. See Cacchiani and Toth (2012), and Caimi, Kroon and Liebchen (2017) for surveys of timetabling models and applications. A key issue for timetabling is the synchronisation of different lines (or different modes) for passenger transfers, which we will discuss in more detail in Section 4.1.

The third planning stage is vehicle scheduling – the assignment of vehicles to service the timetabled trips, with the objective of minimizing cost or the number of vehicles needed. The problem is more complicated for rail than bus because of more restrictive vehicle-type compatibilities and less flexibility in deadheading due to track constraints. Over the years, the computational and algorithmic efficiency improvement have boosted the upper limit of problem size that can be solved. Orloff (1976) modelled vehicle scheduling as an assignment problem and solved a problem with a couple of hundreds of trips in a single depot and dozens of buses; Bodin et al. (1983) extended this problem to over 1000 trips, 100+ drivers in a multi depot setting, solved as a min-cost network flow problem; Löbel (1998) applied an exact solution approach, using column generation with Lagrangean pricing, and solved a problem up to 44 depots and 24906 trips, for the bus system of Berlin. Such optimisation-based approaches are well sufficient for many standard applications. See Bunte and Kliewer (2009) for an overview of vehicle scheduling models and methods.

The last stage involves duty scheduling and crew rostering. A duty is a sequence of scheduled vehicle trips that can be serviced by a driver/crew. Rostering refers to the assignment of duties over a planning horizon (e.g. weeks) to specific personnel. The objective is to minimize personnel costs. The problem is complicated because of the crew-vehicle type compatibilities, restrictions on sign-on/sign-off locations and relief points, and the many complicated work rules. Duty scheduling is typically formulated as a set partitioning problem with the columns (possible duties) generated using the work rules; see, for example, Mingozzi et al. (1999). Wren and Rousseau (1995) presented an overview of the methods for bus driver scheduling and computer systems developed up to the 1990's. More recently, optimisation-based approaches and metaheuristics have been developed; for example, Descrochers and Soumis (1989) introduced a column-generation approach, Li and Kwan (2003) developed a fuzzy genetic algorithm. Heil et al. (2020) surveyed the research on railway crew scheduling since 2000. There has been less work on mathematical models for rostering, although as early as 50 years ago, Bennett and Potts (1968) presented a multi-index assignment formulation, which they solved heuristically for the tramway system in Adelaide. Recently, evolutionary metaheuristics (e.g. Moz et al. 2009; Nurmi et al. 2011) and graph-based approaches (e.g. Lai et al. 2020) have been developed. Ibarra-Rojas et al. (2015) reviewed the literature on bus transport system planning. See the edited volume of Daduna et al. (1995) and the article of Desaulniers and Hickman (2007) for an overview of planning problems for public transit.

With the recent advances in computing technologies, and the availability of data in much finer grain, now we can be more ambitious. Recently, many researchers have investigated, and some leading companies are using, integrated models that combine, if not all four stages, some of the stages of the 4-step process. As early as the 1980's, Ball, Bodin and Dial (1983) developed a computerised procedure to schedule vehicles and crews simultaneously, using a matching-based heuristic. With subsequent advances in computing power and availability of data, exact methods were developed. See, for example, Haase, Desaulniers and Desrosiers (2001) and Freling, Husiman and Wagelmans (2003). Since then, there has been much research development in integrated vehicle and crew scheduling that use a variety of models and methods (See Table 1). The integration involving line planning and/or timetabling is much more complex, but researchers have also begun to tackle models that integrate two "consecutive" planning stages in the past decades. Some cutting-edge researchers have begun to investigate models that integrate three or more planning stages. Table 1 lists some papers on integrated planning since 2010. As can be seen, the models developed are getting more complex, so we can begin to handle anticipated stochasticity or changes in demand, supplemented by the huge amount of big data that are now available.

The contributions of the evolution of computational capabilities and data collection methods are three-fold. Firstly, researchers can handle problems of much greater size and complexity. Modern algorithms are more scalable, robust, resilient, and comprehensive. Ever since the early work on public transport planning problems, there has been a clear research trend from static separated problems to static integrated problems to stochastic and dynamic integrated problems. An early Vehicle Scheduling Problem (VSP) solved is for a single depot with a few hundred trips without considering drivers (Orloff, 1976). The solvable scale of this standard VSP expanded to tens of thousands trips two decades later under a multi-depot setting (Carpaneto et al., 1989). Later VSP variants introduced by Kramkowski et al. (2009); Naumann et al. (2011) provide additional objectives of minimising the failure propagation in the system due to vehicle breakdowns for daily operations with several thousand trips. The other more challenging problem variant made possible is the Vehicle Rescheduling Problem (VRSP), discussed also in Section 6. Every second it takes for the re-optimisation procedure would incur significant disutility for passengers. Earlier research work published (see Li et al., 2007) only allows 100-300 trips to be solved in 1 to 2 minutes by a high-end workstation. More recently, van Lieshout et al. (2018) and Guedes (2018) studied the same problem with respectively 500+ and 2500 trips, solved on personal computers. We also remark that Lagrangean relaxation and column generation remain prevalent approaches over the last few decades. Recent years have witnessed greater solution diversity, spanning from evolutionary heuristics to branch-and-price (Tang et al., 2019).

The second significant contribution is with regards to high-quality data. In most of the world's major cities, smart cards are the mainstream travel ticket, enabling smooth and unbiased travel demand data to be collected. A few decades ago, buses were not tracked by GPS in real-time, and there was no automated toll collection. Some papers back then recognised data insufficiency, for which authors intelligently used probabilistic modelling to compensate (Lampkin and Saalmans 1967; Dubois et al. 1979). These methods are not as necessary in the present time. In the future, algorithms may evolve from pure optimisation to data-driven approaches, involving both the prediction of future demands and optimisation.

Last but not least, fast computation enables real-time reaction. Instantaneous re-optimisation can be triggered whenever external events disrupt the system to prevent failure and delay propagation in the entire network. We will discuss VRSP and other real-time responsive strategies in Section 6.

3.2. School Bus Routing

Unlike general public transit, the demand for school bus service is known well in advance and unchanging from day to day. Trip times and on-time arrival are major concerns. Similar to the case for general public transit, methods and models of school bus routing have evolved with the increasing availability of data and improvement in computational speed. Development of computerised methods for school bus routing began in the 1970's. See, for example, Newton and Thomas (1969, 1970), Angel et al. (1972), Bennett and Gazis (1972) and Bodin and Berman (1979). These early works developed heuristics for designing bus routes from a given set of stops (pickup points) to the school subject to constraints on bus capacity and maximum ride time. The size of the problems involves dozens of routes and a few hundred stops. Interestingly, all these papers discussed the difficulties of obtaining and codifying the data; that was the era before geographical information systems and map visualisations. Two decades later, richer models were developed. Braca et al. (1997) solved the combined routing and scheduling problem for New York City with 839 stops and 73 schools; their problem allowed mixed loads, with students for different schools on the same bus route. Later, Park, Tae and Kim (2012) also investigated the mixed load school bus problem. Other researchers focussed on social objectives instead of only cost minimisation. Delgado and Pacheco (2001) studies a minimax model for minimising the duration of the longest route; Corberán et al. (2002) presented a multi-objective model with the conflicting objectives of minimising cost and minimising the longest route, which was also later studied by Pacheco et al. (2013). Spada, Bierlaire and Liebling (2005) considered the time loss (additional journey time and arrival earliness) compared to a taxi solution for the student. By the mid 2000's, exact approaches for the school bus routing problem were used; see, for example, Bektaş and Elmastaş (2007). In fact, as early as 1984, Swersey and Ballard presented an integer-programming model, but they focussed only on the scheduling problem of assigning buses to routes and solved only the Lagrangian relaxation for problems with 30 buses. By the 2010's, this scheduling problem for up to 135 buses can be solved exactly; see Kim, Kim and Park (2012). The survey paper by Park and Kim (2010) pointed out that the school bus routing problem should be considered holistically as comprising several sub-problems: bus stop selection (and assigning students to bus stops), bus route generation, route scheduling and school bell time adjustment. Except for Desrosiers et al. (1981), prior research had mostly addressed the middle two sub-problems. Recent research have developed more integrated models, and applied exact methods to larger-sized problems. Fügenschuh (2009) presented an integer-programming model integrating school start-time adjustment and bus scheduling which allows transfer of students between routes, solved exactly using cutting planes. Riera-Ledesma and Salazar-González (2012) developed a branch-and-cut algorithm for the combined stop selection and route generation problem. Schittekat et al. (2013) applied a GRASP+VND metaheuristic for this combined problem. Bögl, Doerner and Parragh (2015) developed a heuristic for the problem that integrated stop selection, route generation and bus scheduling, and allowed transfers. Bertsimas, Delarue and Martin (2019) investigated the school bell time adjustment problem for the Boston School District, with over 200 schools, by applying a bi-objective routing decomposition method (that solves the first three sub-problems jointly) to various scenarios of bell times for the schools.

As for public transit in general, the availability of Big Data and IoT technologies have improved the accuracy and reliability of the data for school bus planning, and advances in computational capabilities have enabled more integrated stochastic models to be handled efficiently.

3.3. Pedestrianised City Centres

In many cities, the concentrated city centre is the focus of a variety of activities. Particularly in historical cities, there is a lot of congestion in the city centres, because the streets are very narrow and do not support large volumes of vehicular traffic. One strategy that many such cities have adopted is to turn their city centres into pedestrian-only zones. For such cities, what are the implications for public transport network design? How to efficiently bring peo-

Table 1
Recent research on Integrated Planning (since 2010).

Authors (Year)	Objectives	Constraints	Model/Methods	Data	Key Results
Integration of Vehicle and Crew Scheduling:					
Steinzen et al. (2010)	Minimise vehicle and crew costs	Time-space network; Multi-commodity flow; links between vehicle and crew schedules; capacity; multi-depot	Column Generation with Lagrangean Relaxation; constrained shortest path; Branch&Price	Random instances based on Huisman (2003; 2004) (80 – 640 trips)	Outperformed other methods from the literature on benchmark instances
Mesquita et al. (2011)	Minimise number of drivers and maximum overtime	Vehicle scheduling; links between vehicles and crew schedules; rostering constraints	Non-linear multi-objective; Preemptive goal programming; linear relaxation with Column Generation	Bus company, Lisbon (122-238 trips per day)	A multi-objective integrated approach outperformed sequential approaches; illustrates tradeoffs and parameter effects
Kliewer, Amberg and Amberg (2012)	Minimise total number of vehicles and crew cost	Multi-commodity flow; links between vehicle and crew schedules; maximum allowed flow; time windows; multiple depots	Time-space network; Column Generation with Lagrangean Relaxation; what-if and cutting heuristics	Random instances <http://www.dsor.de/bustestset> Public transit company (80 – 661 of trips)	The proposed approach contributed to enormous reductions in the numbers of vehicles and crews.
Boyer et al. (2018)	Minimise driver and vehicle costs	Driver duty length; rules of driver breaks; compatibility of drivers, vehicles, and trips	Mixed Integer Programming, Variable Neighborhood Search;	Bus system in Monterrey, Mexico FOR2083 2018 (1-25 lines; 7-46 trips per line)	MIP impractical for instances with more than two lines, VNS solved problems with 25 lines in less than 20 minutes.
Ciancio et al. (2018)	Minimise vehicle fixed and deadhead cost	Vehicle routing; vehicle refueling; multiple depots	Simulated Annealing with Local Search	Italian transport companies	Good solutions with a short computational time
Andrade-Michel et al. (2021)	Minimise expected costs of drivers and vehicles and penalty of non-covered trips	Non-overlapping trips and driver breaks; duty length; compatibility among trips, vehicles, and drivers	Constraint Programming; Variable Neighbourhood Search; Monte Carlo simulation	A bus system in Monterrey, Mexico (Boyer et al., 2018) (1-25 lines; 7-46 trips per line)	Substantially increase the number of covered trips, when driver reliability is considered
Perumal et al. (2021)	Minimise operational cost	Coverage of trips; deadheads; driving range of vehicles; labour rules;	Adaptive Large Neighbourhood Search	Electric buses in Denmark and Sweden (2-16 lines; 103 - 1109 trips)	Improve 4% vs. sequential approach; operational costs decrease with increasing electric vehicle range
Integration of Timetabling and Vehicle Scheduling:					
Guihaire and Hao (2010)	Minimise cost of transfer, headway, fleet size, and of deadheading	Given dwell and run times, stop sequences; interlining; turnaround times; service duration	Iterated Local Search with an auction algorithm; simulation	Extra-urban transit in Orleans, France (50 lines; 673 stops; 318 runs; and 282 transfer types)	Improves both service quality and resource levels; part of a commercial decision support system
Ibarra-Rojas and Rios-Solis (2011)	Maximise line synchronization and minimize number of vehicles	Bi-objective formulation	Time windows for transfer; bus bunching; even headways	Private bus network in Monterrey, Mexico, 300 bus lines	A bi-objective formulation is a more representative approach to bus network planning.
Cadarso and Marín (2012)	Minimise operating, investment/leasing cost, crowdedness penalties	Bounds on service frequencies; headways; passenger capacities; rolling stock	Solvers GAMS/CPLEX	RENFE’s regional network in Madrid, Spain (10 lines and around 100 stations)	Integrated approach could achieve a higher degree of robustness; considers crowdedness and capacities
Petersen et al. (2013)	Minimise vehicle scheduling costs and transfer costs	Vehicle scheduling; selection and compatibility of meta-trips	Large Neighbourhood Search	An express-bus network in Copenhagen (up to 8 lines and 1400 trips)	Reduce the passenger transfer waiting times by up to 20%, without affecting vehicle scheduling costs
Schmid and Ehmke (2015)	Minimise deadhead travel times	Vehicle scheduling; maximum total travel time; time windows; balanced departure times	Hybrid Large Neighbourhood Search; Linear Programming	Bus system in Göttingen, Germany (7-14 buses; 49-111 service trips) <http://tinyurl.com/VSPTWBT>	Better solutions in a shorter time, as compared with CPLEX.
Liu, Ceder and Chowdhury (2017)	Maximise simultaneous vehicle arrivals and minimise fleet size	Departure time; headways; transfer synchronization; fleet size	Deficit function-based combined optimization	Numerical example in Liu and Ceder (2017) (2 terminals; 2 routes; 1 transfer stop)	Illustrates the effectiveness of deficit-function graphical optimization to generate Pareto-efficient solutions

(*continued on next page*)

Table 1 (*continued*)

Authors (Year)	Objectives	Constraints	Model/Methods	Data	Key Results
Fonseca et al. (2018)	Minimise the weighted sum of operational and passenger costs	Vehicle scheduling; timetable modifications; links between timetabling and vehicle scheduling; transfer synchronization	Matheuristic	Express bus and trains in Copenhagen, Denmark (up to 8 bus lines, 1585 trips, 360 bus-bus, 1109 bus-train and 1644 train-bus transfers)	Better quality solutions in a shorter time vs. CPLEX. Addition of dwell time could potentially reduce transfer costs.
Carosi et al. (2019)	Minimise bus schedules and costs of deviations from ideal headways	links between timetabling and vehicle scheduling; transfer synchronization	Multicommodity flow; matheuristic; compatibility graphs	Bus lines in Milan (12 bus lines and 2 to 4 terminals)	Approach could aid even experienced planners in constructing better solutions in shorter time with less effort.
Teng, Chen and Fan (2020)	Minimise the standard deviation of departure intervals, vehicles, and charging costs	departure intervals; maximum range electric vehicle; battery charging; precedence	Multi-objective Particle Swarm Optimisation	One bus line in Shanghai, China (168 trips)	Integrated approach reduces the number of vehicles and charging costs, and enhance smoothness of departure intervals.
Schiewe and Schöbel (2020)	Minimise a weighted sum of travel times	Periodic event scheduling; passenger flow	Exact and heuristic preprocessing methods; Solver Gurobi	(i) regional train Lower Saxony, Germany (34 stations; 330 OD pairs; 325,968 pax), (ii) metro Athens, Greece (51 stations; 2385 OD pairs; 63323 pax Friedrich et al., 2017), (iii) long-distance rail Germany (250 stations; 6106 OD pairs; and 385868 pax).	The ratio between the optimal objective values of the problem without routing and the integrated routing was bounded under weak and realistic assumptions.
Integrated line planning and timetabling:					
Szeto and Wu (2011)	Minimise a weighted sum of number of transfers and passenger travel time	Maximum fleet size; frequency requirement; limit on stops; bus interchanges	Genetic Algorithm; neighbourhood search	The bus network of Tin Shui Wai in Hong Kong (10 bus routes)	Method robust under demand uncertainty; integrated approach better than current design and sequential approach.
Kaspi and Raviv (2013)	Minimise total journey time	Prevention of collisions; headways; station capacity; minimum dwell time and transfer time	Cross-entropy metaheuristic	Israel Railways (47 passenger and 30 freight stations; 28 routes) <http://www.eng.tau.ac.il/~talraviv/Publications/ >	The proposed method could reduce passenger journey time by 20%, given the same level of resources.
Goerigk, Schachtebeck and Schöbel (2013)	Minimise costs, maximise number of direct travellers,	Bounds on edge frequencies to distribute frequencies as equally as possible	Simulation platform LinTim (Schiewe et al., 2018)	Intercity rail in Germany: ((i) 250 stops, 326 tracks; 132 lines; (ii) 24421 OD-pairs; and (iii) 319 stops; 452 tracks; 2770 lines; 38939 OD pairs.)	Passenger-oriented line approach yields smaller travel times but is less robust. Cost-oriented models result in more transfers and need more buffer time for robustness.
Burggraeve et al. (2016)	Minimise operator cost and passenger travel time and maximise minimum buffer between trains	Obligatory and operational requirements; links between passenger flows and lines; activity time bounds	An iterative approach which refines solutions between line planning and timetabling models	The S-tog network in Copenhagen (84 stations and 10 lines)	The proposed integrated model improved the robustness of the line plan and the minimum buffer time.
Chu (2018)	Minimise operating costs, passenger paths, and unsatisfied passenger demands	Routing; headway; timetabling; maximum fleet size; transit assignment	Parallel Branch & Price & Cut	Benchmark instances in Mandl (1980) (15 nodes; 42 directed links)	The proposed approach outperformed solver Gurobi.
Steiner and Irnich (2018)	Maximise profit	Links between passenger trips and bus departure times; bus capacity; flow conservation; timetabling	Branch&Cut; valid inequalities	An intercity bus network in Germany (12, 15, and 18 cities)	The integrated approach could offered insights that conventional approaches could not identify.
Yan and Goverde (2019)	Minimise empty-seat-hours, passenger travel time, and number of lines and stop patterns	Capacity; train frequencies; timetable periodicity and regularity; running and dwell times; headways; non-collision; robustness; overtaking	An iterative approach which refines solutions between line planning and timetabling models	Shanghai to Nanjing highspeed railway (14 stations; 268 types of stop patterns)	Better robustness than one-hour periodic timetable; Proposed approach with extended period length provide the best timetable regularity and robustness.

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Table 1 (*continued*)

Authors (Year)	Objectives	Constraints	Model/Methods	Data	Key Results
Blanco et al. (2020)	Minimise capacity cost, maximise served passenger	Train capacities; time control; flow control; cost of unserved passengers	Time-dependent piecewise linear demand functions; matheuristic	1. Paris subway network (2 lines, 9 stations). 2. Artificial network (2 to 8 lines and 7/14 stations).	Matheuristic algorithm had comparable performance with the mathematical programming approach.
Integration with Passenger Routing:					
Schmidt and Schöbel (2015)	Minimise the total passenger travel time	Bounds on activity times	Reformulation; complexity analysis; solver Gurobi	1. Athens, Greece metro; 2. German Rail <https://www.lintim.net/ >(up to 218 OD pairs; 319 stations; 452 direct connections; 723 transfers)	Joint problem models passengers' behavior more accurately and yield better quality solutions. Integrated problem could be modified to be polynomial-time solvable.
Bull et al. (2016)	Minimise passenger travel time and operating line cost and maximize the number of direct travellers	Assignment of lines to frequencies; budget constraints; bounds on the number of trains at a station; flow conservation	Limited pool of lines; Linear Programming heuristic	S-tog Copenhagen (174 lines; 258 incompatible lines; 350 line-frequencies; 4645 OD pairs; 189 operation requirements)	Arc-flow model produced solutions of reasonable quality. LP heuristic could produce good solutions in a short time.
Gattermann et al. (2016)	Maximise the total reduction in maximal travel times	Timetabling; links between paths and activities; routing	Reformulation as partial weighted MaxSAT problem	Long-distance rail in Germany (158 periodic lines; 181 stations)	Integrated model provided better solutions than the traditional approaches.
Borndörfer, Hoppmann and Karbstein (2017)	Minimise passenger travel time and maximum weighted travel time among all passengers	Periodic timetabling; capacities on passenger flows;	Solvers SCIP and CPLEX	Wuppertaler Stadtwerke Germany (158 stations; 229 nodes; 460 arcs; 45254 OD pairs; 67 bus lines; 3 train lines; one cableway).	The impacts of passenger routing models in the optimization were substantial.
Goerigk and Schmidt (2017)	Minimise the total cost of train lines and total passenger travel time	Transportation capacity; flow conservation	IP with lazy constraints solved by CPLEX; Genetic Algorithm	German long-distance network (250 stations; 132 lines) <https://www.lintim.net/ >	IP approach could reduce computational times. Genetic algorithm could solve large-scale problems.
Owais et al. (2021)	Maximise direct demand and minimise total transfers and uncovered demand	Passenger transfers	Planning software TransCAD; Passenger transfer counting algorithm	The transit network in Greater Cairo, Egypt (88 metro stations; 98 bus stations; 12 bus lines)	The ring lines were efficient in reducing passenger transfers between stations with the minimum construction cost.
Integration of several planning stages:					
Michaelis and Schöbel (2009)	Maximise average probability of traveller using public instead of private transport	Fleet size; capacity of a bus stop; breaks for drivers; slack times in the timetable	Three-phase heuristic: routing, splitting routes to lines, and timetabling	A German local bus company Göttinger Verkehrsbetriebe (485 stops; 248 locations)	Some parts of the solution were implemented in Göttinger and had good performance.
Schöbel (2017)	Minimise operating costs, travel times, and number of transfers	Bounds on frequencies; duration of driving; waiting; transfer; vehicle scheduling	Eigenmodel	N/A	General convergence results were proven.
Laporte et al. (2017)	Minimise traveller inconvenience, line runs costs, and fleet size costs	line runs capacity; compatibility of strategies; budget; requests capacity; vehicle scheduling	ϵ-constraint method	Laporte et al. (1994) and Laporte et al. (1997) (13 nodes; 12-16 edges; 100 transportation requests)	Method provided the allocation of transportation requests to their optimal strategies given capacity.
Long, Luan and Corman (2021)	Minimise total train operating cost and passenger utility	Timetabling; rolling stock; passenger routing	Approximation and exact reformulation of the Mixed Integer Non-linear Programming solved by CPLEX	Artificial network (2 lines; 9 stations)	Exact reformulations gave higher quality solutions vs. approximate/exact methods. Reduce use of emergency trains.

ple from the outer areas of the city to the town centre? Many cities adopt a "Park and ride" approach, where people drive to a suburban parking area and then ride public transit into the city centre. Other cities, such as Hong Kong, may have local shuttle buses that connect to a backbone rail network to access the city centre. For such multi-modal networks, the main backbone line might have a much higher capacity than the feeder services. Coordination of the design and operations, in terms of capacity and schedule frequency, of these multi-modal networks is an important issue.

A smart city with more services and interactions carried out online may obviate the need for in-person trips to the city centre. If smart cities adopt a distributed town-planning concept, where work and play activities are focussed on a local community basis, that would have important implications on the overall design of the public transit service network.

In summary, with the increased sophistication in our models and methods, we can also be more ambitious in our goals. When designing a public transport service for a smart mega-city, perhaps one should not just think of moving people from origin to destination as how planning was done in the past, but one should take an urban planning perspective and think about what people want to do in the cities, and how public transport can support those activities. Perhaps public transport planning should be more activity-focussed and not just transport-focussed per se.

4. Mobility

By mobility, we mean that the public transport system must support passengers' desire to travel from their origins to their destinations in a direct way at the time that they want. Passengers do not want to spend a lot of time on circuitous routes to get to where they want to go.

This means that the public transport system must provide passengers with convenient departure times, short journey durations with minimal interchanges. To support this, the network design and scheduling of the system must be well-planned, particularly in relation to the co-ordination of the schedule and capacity between the feeder and backbone network. Adjusting the schedule to manage the rush-hour peaks is also important. Many metro services have shortened lines and/or express services during rush hours, in order to offer speedier service between key locations.

Even within a backbone metro network, there may not be a direct line from one's origin to the destination, and transfers between train lines are necessary. For cities with a concentrated city centre, e.g. Athens, it may be sufficient to design the network with lines that radiate out from the city centre to the outskirts residential areas, offering a direct route for most commuters. Some other cities may not have a single city centre but several main central business districts (for example, Shenzhen has 4 CBDs), so the origin-destination patterns are more complex. For large cities, a single central transfer hub may be too congested to provide efficient service. For metropolitan areas with several "centres", the public transport system often include a circular line intersecting with other radial lines to provide broad coverage, e.g. the Circle Line in London, the Yamamote Line in Tokyo. The metro system in a mega-city is typically a labyrinth of crisscrossing lines, with hundreds of stations, further complicated if the lines are run by different companies. There, a passenger definitely has to interchange during a trip. This leads to the problem of synchronization among the different lines. Balancing the timetable of the many lines with multiple transfer stations is a very complex problem. Mixed-integer programming has been the main approach for timetable synchronisation for urban rail and metro system. Recent models have included capacity and crowdedness considerations. Unlike trains running on dedicated tracks, travel time variation is more of a problem for buses, so stochastic models are more common for bus timetabling. See Table 2 for some recent research.

4.1. Timetable Synchronization

Just focusing on the problem of co-ordination of transfers within a public transit network, there has been much research in the past decades. Klemt and Stemme (1988) and Domschke (1989) were the earliest researchers to consider schedule synchronization for public transit networks, modelled as a quadratic assignment problem. Bookbinder and Désilets (1992) considered minimising the disutility of transfer waiting time for a transit network with stochastic bus arrival time. Nachtigall and Voget (1996) investigated synchronization for periodic timetables. Ceder, Golany and Tal (2001) investigated timetable design to maximise the number of simultaneous bus arrivals. Other researchers also worked with transit providers to design timetables for smoother passenger transfers. See, for example, Liebchen and Möhring (2002) and Liebchen (2008) for the Berlin subway; Jansen, Pedersen and Nielsen (2002) for the Copenhagen-Ringsted line; Vansteenwegen and Van Oudheusden (2006) for the Belgian railway; Wong et al. (2008) for the Hong Kong Mass Transit Railway.

Table 2 gives a summary of recent research on timetable synchronization for both rail and bus transit. As indicated, the models are getting more complex and more realistic. All these studies show that if we design the timetable to minimise the interchange time, it makes for a better ride experience (shorter waiting time, hence shorter journey time) for the passengers, it reduces the crowdedness at stations **and** allows the system to carry more passengers. The recent paper of Yin et al. (2021) also raises the network design issue of where passengers should transfer/interchange.

The public transport system in a smart city involves many different modes – rail, bus, taxi, bicycles – with both fixed timetables or flexible despatch. Planning should be done holistically system-wide. In the coordination between different transport modes, there are several issues of concern. Firstly, are the capacities and frequency of the connecting modes commensurate? Secondly, are the timetables synchronised to offer a smooth transfer? Thirdly, are the multi-modal route options attractive to the traveller? If multiple options are available, how to induce particular route choice and travel behaviour (for social welfare or other purpose)? Lastly, where should the transfer points be located, especially for modes with routes that overlap? More generally, the overall line planning for all the transport modes shoud be done in an integrated manner. Much of the research on feeder services only address the first question when setting frequencies and fleet size. Few papers (only 2 among the ones reviewed in this paper) have addressed the second question of time table synchronisation for multi-modal transfer. Parbo et al. (2014) determined the timetable offset of buses to minimise the weighted transfer time. Takamatsu and Taguchi (2020) also studied timetable synchronisation for buses connecting to/from trains, and found that extending dwell times improves transfers in both directions. On the thrid questions, studies (e.g. Schakenbos et al. 2016) have shown that travellers consider other factors in addition to total travel time when choosing among different multi-modal choices. Bertsimas et al. (2020) is one of the first papers to study joint frequency setting and pricing optimisation for multi-modal transit networks. The problem of how to induce route choice and travel behaviour, to balance crowdedness among lines or to encourage green lifestyles, is an interesting but little explored area of research. Similarly, there has been little research on the last question, although an important one for a smart city. IoT technologies have enabled fine-grained tracking of itineraries, provided detailed temporal and spatial information that should be exploited in the planning and design of public transport service. Urban design

Table 2
Recent research on Timetable Synchronisation (since 2010).

Authors (Year)	Transit Mode	Objectives	Constraints/ Problem Features	Model/Methodologies	Data	Key Results
Shafahi and Khani (2010)	Bus	Minimise total transfer waiting time	Average and minimum waiting time limits; Adjust stop time at bus stops; Consider in-vehicle time;	Mixed integer program; solved by CPLEX; genetic algorithm	Mashhad City, Iran (139 two-way bus lines; 3618 bus stops, 841 transfer stations)	Extra vehicle stopping time at transfer stations can reduce total transfer waiting time
Ibarra-Rojas and Rios-Solis (2012)	bus	Maximise number of synchronisations	Bounds on headway times and avoid bus bunching	Pre-processing techniques; iterated local search	Monterrey's bus network in Mexico (15 - 200 lines; 3-40 nodes)	High-quality solutions obtained for realistic problems in less than one minute.
Saharidis, Dimitropoulos and Skordilis (2014)	bus	Minimise total waiting time	Arrival/departure times; route start/end times; Headways; Bounds on turnaround times; Allow transfer to more than first available bus;	Mixed integer linear programming solved by CPLEX	Crete bus network in Greece (122 nodes)	Average waiting time reduced by 50% over existing timetable.
Parbo, Nielsen and Prato (2014)	Bus, train. Metro. S-train	Minimise weighted waiting time	Regular headways; No overtaking; dwell time; Adjust offset of bus lines,	Bi-level minimisation, non-linear non-convex mixed integer problem; tabu search	Public transit network Denmark (1794 lines with 8373 variants, 22187 stops; including 1440 bus lines with 7877 variants and 21396 bus stops)	The proposed approach could significantly reduce the weighted transfer waiting time.
Wu et al. (2015)	urban subway	Minimise the maximum weighted transfer waiting time	Headway; running time; dwell time; bounds on waiting times Equitable waiting time (min-max);	Genetic algorithm	Beijing subway network (8 double track urban lines; 18 transfer stations)	Easy to implement; by optimising the max transfer time, the average waiting time was also reduced.
Guo et al. (2017)	metro	*Maximise synchronizations in transitional period*	Arrival and departure times; dwell time; time windows; headways; transfer efficiency; train synchronisation time	Mixed integer nonlinear model; particle swarm optimization; simulated annealing	Beijing metro network (42 transfer stations; 16 lines)	A coordinated and balanced timetable to reduce passenger travel time, for a smooth transition between peak and non-peak hours.
Liu and Ceder (2017)	general	Minimise costs from both user and operator perspectives	Bundle departures; fleet size; headways; load discrepancy; Multi-objective: passenger in-vehicle travel time, initial and transfer waiting time, and vehicle costs;	Bi-objective nonlinear integer programming model; deficit-function, sequential search, Pareto-efficient solutions	Artificial network (2 terminals; 2 routes; 1transfer stop)	The proposed method was effective in practice and had potential to be applied for large-scale and realistic problems.
Liu et al. (2018)	Metro	Minimise transfer waiting time	Fixed running times, dwell times and headways;	Simulated annealing with parallel computing	Shenzhen metro, China (10 lines; 262 stations); data from automatic fare collection system	The proposed method could significantly reduce transfer waiting time.
Shang et al. (2018)	subway	Minimise total travel time of all passengers	passenger loadings; headways; running times; dwell times; time-dependent passenger demands	Genetic algorithm; binary variable determination method	Beijing subway (12 lines; 14 transfer stations; 28 other stations)	Larger adjustments of operational parameters could better adapt to time-dependent passenger demands.
Tian and Niu (2019)	high-speed rail	Maximise connections, minimise transfer waiting time	Irregular headways; Arrival and departure times; dwell times; headways; train synchronisation	Bi-objective integer programming; sequential search algorithm	Artificial network (3 lines; 8 stations; 9 – 560 trains)	Longer headways increase the number of connections.
Cao et al. (2019)	Urban rail	Maximise the number of synchronized transfers	Periodic; Arrival and departure times; headways;	Mixed-integer program; Genetic algorithm with local search	Beijing urban rail (16 double-track lines, 235 stations, of which 40 are transfer stations)	Proposed metaheuristic perform better than exact methods, esp. for large problems
Chowdhury and Chien (2019)	general	Maximise operator's profit	Demand elasticity; passenger demands; wait time; transfer and In-vehicle time; capacity;	Nonlinear model; derivative-free iterative search	Artificial network (4 bus routes)	Fare and headways can be optimised to maximize profit.

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Table 2 (*continued*)

Authors (Year)	Transit Mode	Objectives	Constraints/ Problem Features	Model/Methodologies	Data	Key Results
Wu et al. (2019)	Bus	Minimise system cost and expected travel disutility	Induced slack times, missed/daelayed connections, initial/ transfer waiting and in-vehicle time; transfer failure rate; passenger rerouting	Bi-level programming model, Mixed integer nonlinear program; method of successive averages, heuristic	Artificial networks: (3 routes; 18 links; 9 nodes, of which 3 are transfer stations), (4 lines; 3 transfer stations)	Schedule coordination was more effective, with fewer slack times when demand assignment and passenger rerouting behavior was considered.
Li, Luo and Cai (2019)	Last train with taxi and bus	Maximise passenger flow	running time; dwell times; last train departure; forecast demand via GPS taxi & bus smartcard data;	Genetic algorithm	Shenzhen Metro (8 transit lines; 199 stations)	More co-ordination with 20% more passengers connected transfers than the original timetable.
Takamatsu and Taguchi (2020)	bus with train	Maximise transfer passengers' gains over loss for direct passengers	Adjust arrival/ departure times; Max connections, minimise trip time; Travel time; waiting time; transfer time	Event-activity network model;	Buses in Tohoku District, Japan (803 stops; 258 lines; 88 train stations)	Mutual connections could smooth transfers in areas with low traffic demand and infrequent public transport services.
Abdolmaleki, Masoud and Yin (2020)	bus	Minimise total transfer waiting time	Adjust terminal dispatch time; Fixed headways, dwell times and run times	Euclidean algorithm; Local Search; Congruence constraints;	Mashhad Iran city bus (278 lines; 3618 stations, of which 841 are transfer stations)	The proposed method outperformed state-of-the-art algorithms.
Gkiotsalitis, Eikenbroek and Cats (2020)	Bus	Minimise aggregated difference between actual and ideal half-headways	Minimum layover times; minimum and maximum dispatching headways; schedule sliding;	minimax optimisation model; robustness; approximation via relaxation	1. Artificial network (2 bus lines) 2. Bus network, the Hague, Netherlands (16lines)	The proposed method could potentially improve regularity and synchronisation under both regular and extreme conditions.
Wang, Li and Cao (2020)	Rail	Minimise failed transfers, and initial and transfer waiting time	Arrival and departure times; headways; train choice; transfer; Train capacity, time-dependent demand, non-transfer passengers;	Non-linear mixed-integer model; genetic algorithm, grey wolf optimiser	1. Artificial network (2 lines; 4 stations) 2. Shenyang rail transit, China (2 lines; 22 stations)	The proposed approach could reduce non-transfer passenger waiting time, transfer waiting time, and failed transfers.
Ataeian et al. (2021)	Bus rapid transit	Maximise synchronized arrivals and minimise fleet size	Arrival times; headways; Adjust terminal dispatch times; Arrival times; headways	Bi-objective mixed integer nonlinear program; genetic algorithm NSGA-II	1. Artificial network (4 lines; 6 stops) 2. Tehran bus rapid transit, Iran (8 lines)	Proposed method yields Pareto optimal solutions for both small and large bus networks.
Yin et al. (2021)	Rail transit	Minimise the highest congestion level	Passenger boarding; Capacities by passenger type; headway; rolling stock;	Mixed Integer Programming; adaptive large neighbourhood search	1. Artificial network (2 lines; 18 stations) 2. Beijing urban rail (3 lines; 44 stations)	Proposed approaches could reduce crowdedness as compared with the current practice.
Nesmachnow and Risso (2021)	Bus	Maximise number of successful transfers	Extended bus transfer zones; Uneven headways; Arrival times; headways	Mixed integer program; Evolutionary algorithm	Montevideo, Uruguay (250 lines; 30 – 110 transfer zones) <https://www.fing.edu.uy/inco/grupos/cecal/hpc/bus-sync/#main.md >	The proposed method could significantly improve synchronisations (over 150%) and average waiting time for transfers.
Hao, Song and He (2021)	urban rail transit	Minimise detained passengers, traveling time, max detention rate	Variable running times and dwell times; Train capacity; Objectives include transfer waiting time, detained passengers on platform, and largest detention rate;	Simulation-based optimisation; Mixed logic dynamic model; Adaptive Genetic Algorithm	1. Artificial network (3 lines; 10 stations) 2. Metro of Chengdu, China (4 lines; 81 stations)	Demand management strategy of controlling boarding to balance flow was effective in coordinating timetables in a congested urban rail transit network.

and the layout of the city strongly impact the inducement of usage of different travel modes. It is a delicate balance of service quality, costs and environmental concerns when designing the public transport system to support the activities of the people in a city. The more integrated planning we do, the better off the passengers might be.

4.2. Demand-Adaptive Transit

A traditional public bus system has fixed routes run to a timetable. For areas or time-periods with low demand, the bus may be visiting many stops without any passenger pick-up or drop-off. This is not cost-effective for the operators; on-board passengers also prefer more direct and shorter journeys to their destinations. Malucelli et al. (1999) introduced a Demand Adaptive System (DAS), where a transit line has compulsory and scheduled stops (similar to regular bus lines) and a set of optional stops. Passengers may request service specifying the origin-destination stops. The vehicle only visits the optional stops upon requests, otherwise, it travels along the shortest path between the compulsory stops. They presented three formulations that addressed request selection, assignment of request to different runs and alighting stop adjustment. Crainic et al. (2001) and Crainic et al. (2012) further investigated the network design and scheduling of the DAS. Quadrifoglio et al. (2007) and Quadrifoglio et al. (2008) studied a Mobility Allowance Shuttle Transit (MAST) service where passengers may request specific pickup-dropoff times and locations (vs. operator listed optional stops). This was motivated by safety concerns of the night-time service of Line 646 in Los Angeles, so passengers do not have to walk to and wait at bus stops. They presented heuristics and mixed-integer models and solutions for the problem.

Errico et al. (2013) presented a survey of demand-adaptive semi-flexible transit systems, where they highlighted that the planning issues — for service area coverage, line planning, timetabling, operations —- are different from traditional systems with fixed routes and schedules, due to the uncertainty and flexibility. Many of the models and analyses are based on (simplified) probabilistic assumptions about the demand. All of the systems studied require advance request for service. For a Smart City, can the acceptance decisions for requests be made in almost real-time? This may mean forgoing computationally intensive stochastic optimisation models for faster heuristic online algorithms. As more lines switch from fixed routes to such demand-adaptive routes where arrival times at stops may be more variable, the design and synchronisation of transfer between lines become more important, especially for multi-modal transfer between the more flexible bus lines and the more rigidly timetabled rail service. As demand for flexible service increases, there arises a new problem of aggregation of requests to consolidated pickup/dropoff locations, which has to balance operational efficiency and customer service quality (additional walking to stops but perhaps shorter journey time). Providing flexibility and customisation for public transport in a Smart City introduces new opportunities and challenges.

5. Accessibility

By accessibility, we mean the ease of access to public transport and a smooth and comfortable ride. Of course, passengers desire a door-to-door service on-demand at their convenient time. What is required of the system design is co-ordination between feeder network and backbone network in capacity and in service frequency, and wide coverage of access locations. When we have unlimited resources with no regard to cost, of course, it is easy (or at least easier) to provide that. Demand in the outer reaches of the city is not so high, so it is difficult to provide cost-effective service. In freight, this is called the “last-mile” problem; the cost of the last-mile delivery is more than half the overall shipping cost. How can the public transport system offer access for rural and suburban areas with low demand without the passengers having to wait too long for the bus/train? In this section, we discuss some recent innovations and research to address this question.

5.1. Demand-Responsive Feeder Services

Feeder transport services were proposed as early as 1980s (Kuah and Perl, 1987; 1989), where integrated feeder-bus and rail rapid transit services demonstrated the benefits such as reduced cost and improved service quality. Since then, extensive research on feeder services, such as network design (e.g., Martins and Pato, 1998), scheduling (e.g., Quadrifoglio et al., 2008), coordination of feeder services with main transit (e.g., Shrivastava and O'Mahony, 2006) has been conducted. In most of these applications, feeder buses were considered. Table 3 presents recent research on feeder services (since 2017). Traditional feeder services such as feeder buses and shuttles are still the main types of vehicles to provide the first/last mile transportation services.

Several researchers have investigated systems that couple dial-a-ride services with scheduled fixed-line services. Liaw et al. (1996) developed a decision-support system to determine the paratransit routes and the transfer points to the fixed bus routes, tested for the system in Ann Arbor, Michigan. Hickman and Blume (2000) developed a scheduling algorithm for the problem. Aldaihani et al. (2003) used tabu search to design passenger itineraries and vehicle routes, tested on data for the Antelope Valley Transit Authority in California. See, also, Uchimura, Takahashi and Saitoh (2002), Häll et al. (2009), Posada, Andersson and Häll (2017), Lee et al. (2019) and Molenbruch et al. (2021). Aldaihani et al. (2004), Li and Quadrifoglio (2011) developed analytical results to determine the optimal DARP service zones and fixed routes for a square grid with a uniform demand distribution.

Montenegro, Sorensen and Vasteenewegen (2020, 2021) have investigated a Demand Responsive Feeder Service. The idea is to have a feeder service that connects people to a key “destination” station on the main metro backbone network, from whence they can then travel to other places. This feeder service has a main route with regular (mandatory) stops where people can get on, just like a standard feeder bus service. Passengers who are further away from this main route can book ahead to request service. They would then be told which *optional* stop to go to catch the bus service. Correspondingly, the bus will “detour” to these optional stops, which it would not visit without prior appointment. This is one way that we can balance the operating cost and offer good service to the customers in low demand areas. Lee and Savelsbergh (2017) showed that the flexibility of allowing alternate “destination” mainline stations reduced costs with minimal added passenger inconvenience. The design of the bus routes, the location of the optional stops and the assignment of the passengers to routes and destinations are interlinked research questions.

A significant research trend on feeder services is the deployment of autonomous vehicles (e.g., Scheltes et al., 2017; Fielbaum, 2020; Zhang et al., 2020; Shan et al., 2021), due to the maturity of the technology. A key advantage of feeder services is to deploy transport units with smaller capacities to efficiently address low passenger demands from/to certain origins and destinations. Transport accessibility and equity can, therefore, still be ensured. See, for example, Gorev et al. (2020), Schlüter et al. (2021) and Sörensen et al. (2021). A kind of recent novel technology, which is often operated autonomously, is modular vehicle; see, for example, Chen and Li (2021), Gong et al. (2021) and Pei et al. (2021). Each modular vehicle can be docked or undocked with other modular vehicles to dynamically adjust the capacities to serve passen-

Table 3
Recent research on Feeder Services (Since 2017).

Authors (Year)	Application	Objectives	Constraints	Methodologies	Data	Key Results
Design of feeder services						
Scheltes et al. (2017)	Connection of Autonomous Vehicles with trains for last mile transport	Minimise the passenger travel time	Vehicle constraints; recharging at depots constraint	Agent-based simulation	Delft, Netherlands (13 centroids; 941 respondents surveyed in the station)	Personal passenger rapid transit for last-mile service, encouraged the use of metros.
Zhu et al. (2017)	Demand model with evaluation of passenger flow distribution	Maximise potential demand of the feeder service	Road network constraints; maximum travel time	Logit model; Genetic Algorithm	Feeder bus service for urban rail transit stations in Shanghai (5 regional areas)	Proposed method could analyse links and outline potential demands for feeder services.
Charisis et al. (2018)	Design of Demand Responsive Transit for last mile transport problem	Minimize routes, travel time and passengers not served	Road network constraints; capacity; flow conservation	Genetic Algorithm	DRT in Athens, Greece (3 metro stations; 15 bus stations)	Proposed method was effective, efficient, and robust in designing bus routes.
Jara-Díaz (2018)	Design of urban line structures with trips to central business district	Minimise fleet and operating cost; Evaluate network design	Road network constraints; passenger demands fulfilment	Analytical modelling and optimisation	Artificial instances (Up to 40000 passengers)	Direct lines and hub-&-spoke more efficient than feeder lines when population large and long trips dominate.
Park et al. (2019)	Feeder bus route planning for replacement of taxis	Maximise similarity between taxi service and potential public transport routes	Road network constraints	Road2vec; K-means clustering; Integer Programming	Taxi in Seoul, South Korea (142 intermediary stops; 60000 roads; 45264 trajectories)	Public transport routes identified provided better coverage of residential areas, transit stations and schools.
Calabrò et al. (2020)	Feeder bus routing	Maximise fulfilled demand	Road network; Maximum travel time	Ant colony optimization; multi-agent simulation	Weak demand areas in Sicily, Italy (300,000 people; 2 routes).	Proposed method was valid and provided suggestions for future designs and operations
Chen, Hu et al. (2020)	Feeder Electric Bus services design with charging constraints	Minimise the costs of charging devices, battery, operation, and travel time	Bus routing; battery charging	Mixed Integer Linear Programme; nested Genetic Algorithm	Xian, China (3 – 23 charging devices; 38 potential bus stops)	Electric fleet operating cost lower with dynamic wireless power transfer at bus stops than charging at terminal.
Chen, Li et al. (2020)	Joint design of vehicle headway and vehicle capacity (with modular vehicles)	Minimise energy and waiting costs	Minimal headway; vehicle capacity; departure curve conservation; feasible region	Continuum approximation (CA) model	Shuttle systems Beijing, China, (18.96 km, 13 stations); Tampa and Palm River-Clair Mel, USA	The CA model extended to oversaturated traffic situation.
Deng et al. (2020)	Design of bus feeder routes and frequencies	Minimise passenger transport costs and operating costs	Road network constraints; bus capacity; bus operation time	Genetic Algorithm	China (4 rail transit stations; 80 bus stops; 200 passengers per bus stop)	Proposed method efficiently solved the problem of connecting multiple bus stops to multiple rail transit stops.
Fielbaum (2020)	Examination of potential improvements with Autonomous Vehicle feeder services	Minimise resource required	Road network constraints; capacity constraint; Adjust bus lines and frequencies, fleet size,	Analytical modelling	Santiago, Chile. (553,000 passengers; 26201 trips per hour; 6154 buses; 184 metro trains)	Model dynamically respond to demand. AVs encourages larger fleets of smaller vehicles and more direct routes
Jiang et al. (2020)	Insights into bus feeder service design	Balance minimising travel time and number of stops	Different line configurations are analysed	Analytical modelling and simulation	Artificial instances (4 KM^2 service region; 5000 KM^2 demand groups of 80 passengers each)	Study reveals the relationship between width of study area and number of fixed stops, travel demands and routes.
Zhang et al. (2020)	Feasibility of modular transit service for first- and last- mile transport	Maximise number of served rider requests	Capacity constraints; network constraints; Main vs. trailer modules usage	Mixed Integer Linear Programme solved by CPLEX; graph partitioning technique	Sioux Fall network (9 stations; 50 – 500 rider requests); NYC taxi dataset < http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml > (184 stations; 4000 riders)	Performance of modular bus feeder services was better than traditional bus services.

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Table 3 (*continued*)

Authors (Year)	Application	Objectives	Constraints	Methodologies	Data	Key Results
Chen and Li (2021)	Design of transport corridor systems with Modular Autonomous Vehicles	Minimise passenger waiting costs	Minimal headway; onboard passenger conservation; network constraints; capacity adjustable at every station	Customised Branch and Bound	(Mandl, 1980) (15 nodes); Beijing subway (13 metro stations; 100 – 500 passenger arrival per minute)	Modular Autonomous Vehicles were more flexible.
Dakic et al. (2021)	Flexible bus dispatching system for fully automated buses	Minimise fleet size and maximise fulfilled demands	Operational budget; traffic restrictions	Vehicular dynamics	Modular bus Zurich, Switzerland (5 bus lines; 50 conventional buses)	AV System was flexible and significantly outperform the existing bus system.
Gong et al. (2021)	Customised modular bus system design	Minimise travel distance and maximise served demands	Vehicle capacity; passenger transfer; maximum travel time; fleet size	Mixed Integer Non-linear Programme; Particle Swarm Optimisation	Sioux Falls (24 nodes; 38 bidirectional links); Chengdu, China (30 – 153 stations; 300 buses)	Proposed method could efficiently solve the non-linear problem after linearisation.
Wang, Zeng et al. (2021)	Incentive model for customised buses	Minimise the cost of routing	Time windows; capacity; Passengers offered incentives to change O-D locations, to aggregate demand	Discrete choice and vehicle routing models	Shanghai, China (96 respondents; 404 stated preferences and 4233 valid choice samples)	The proposed method improved fulfilled demands and profit.
Xiong et al. (2021)	Design of community bus services (routes, frequencies, and vehicle capacity) as feeder to metro	Minimise transit system and supplier costs	Route length; coverage area; vehicle capacity; fleet size	Genetic Algorithm	Huilongguan, Beijing, China. (4.8km x 2.2km; 106 nodes; 1 bus depot; 55 bus stops; 6 metro stations)	Genetic Algorithm could solve the problem efficiently.
Operations of Feeder Services						
Montenegro et al. (2021)	On-demand bus services	Minimise travel time, passenger walking time, and difference from target arrival time	Capacity; time windows	Large Neighbourhood Search	Artificial instances (24 buses; 158 requests; 67 stops)	Demand Responsive Transit service could improve service quality over traditional service by 60%.
Pei et al. (2021)	Modular vehicle dispatching	Minimise overall system cost (operational and passenger trip time)	Vehicle capacity; pod conservation; flow conservation	Mixed Integer Non-linear Programming; linearized model solved by Gurobi	Public transit Guangzhou, China (10 critical bus stops); Guangdong Province freeway (19 stations)	Modular transit network system design reduced the waiting time by up to 25% and operational costs by 81%.
Liu et al. (2021)	Flex-route transit services with Modular Autonomous Vehicles (MAV)	Minimise operation, purchase, and ride costs	Flow conservation; time constraints; passenger assignment; Mixed Integer Linear Programme formulation	Two-stage approach: ((i) Dynamic Prog. with valid cuts and (ii) DARP heuristic	Bus system in Beijing, China (132 bus lines, 15 stops; 20 MAVs; 5 traditional vehicles)	This new mode of Autonomous Vehicles was more flexible and could serve demands better.
Shi and Li (2021)	Design of modular vehicles services	Minimise passenger waiting and operator operational costs	Vehicle dispatch; capacity; first in first out	Mixed Integer Linear Programme; dynamic programming	Beijing line 6, China (19 stations; 50 modular units)	Proposed Dynamic Programme outperformed Gurobi in both solution quality and time.
Wang. Yu et al. (2021)	Routing and scheduling of a responsive feeder transit system	Minimise operational costs	Capacity; time; demand constraints; route adjusted for real-time requests	Adaptive Genetic Algorithm	Metro Line 1 in Changsha, China (20 nodes; 10 vehicles; 85 passengers)	Batch processing of real-time demand reduces re-routing frequency but decrease response to passengers.
Coordination of Multi-modal Transport Networks						
Almasi et al. (2018)	Design of railway and feeder bus systems	Minimise user waiting costs and operator costs	Feeder route length; frequency limitation; fleet size; route upper limit	Simulated Annealing; Genetic Algorithm; non-dominated sorting GA II	Kelana Jaya Line at Kuala Lumpur railway, Malaysia (5.5×6.5 KM^2, 54 nodes)	Pareto optimal solutions obtained for the multimodal (bus and van) feeder network design problem with multiple objectives.
Bertsimas et al. (2020)	Joint frequency setting and pricing in multi-modal transit networks	Minimise user waiting costs	Operators' budget; capacity constraint; passenger preference	Discrete choice model; non-linear optimization solved by Gurobi	Tokyo, Japan (57 stations; 5 lines; 70,000 passengers); Boston, USA (4 lines; 74 stops; 95760 commuters)	The proposed method could jointly optimise pricing and frequency problems.

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Table 3 (*continued*)

Authors (Year)	Application	Objectives	Constraints	Methodologies	Data	Key Results
Manser et al. (2020)	Dynamic Demand Responsive Transit services in a multi-modal network;	Maximise profit	Political constraints (Subsidies and penalties)	Agent-based simulation and co-evolutionary algorithm	Public transport network in Zurich, Switzerland (160,000 agents)	The proposed method could assess public transport policies (e.g., subsidies).
Salazar et al. (2020)	Autonomous mobility-on-demand with public transit	Minimise passenger waiting costs and maximise profit	Road congestion; flow conservation	Network flow model; pricing and tolling schemes	New York City, USA (8678 OD pairs); Berlin, Germany (2646 OD pairs)	Better-connected network in Berlin resulted in better service quality and lower emissions.
Shan et al. (2021)	Joint optimization of railway transit network design and Shared Autonomous Vehicle feeder service	Balance cost and accessibility	Flow conservation; time constraints; capacity	Non-linear Mixed Integer Programming; Fixed Point algorithm	Artificial instances (4560 commuters, $1.5\times1.5\ KM^2$; 9 clustered regions; up to 666 vehicles)	Joint optimisation of railway transit network and SAV first mile service more cost-effective and robust.
Policies on Feeder Services						
Alonso-González et al. (2018)	Assessment of Demand Responsive Transit services	Comparison of demand-responsive vs. fixed transit	Evaluate generalised journey time, declined trips	Empirical study	Netherlands (255 stops; 4719 performed trips; 130 declined ones)	Evaluation framework for DRT services and identify important factors.
Gorev et al. (2020)	Demand Responsive Transit (DRT) systems in areas with low transport demand;	Assess feasibility of replacing traditional buses with demand-responsive transit	Not described	Qualitative analysis	N/A	Telecommunications technology could make public transport more flexible. Integrating traditional transport and DRT is best.
Merkert et al. (2020)	Collaboration-as-a-Service	Assess integration of transport systems	Identify mechanisms for collaboration	Qualitative analysis	N/A	Integration and collaboration between public operators and private companies could make system more efficient.
Reck and Axhausen (2020)	Subsidised ridesourcing feeder services	Evaluate the Value of Travel Time Savings (VTTS) for ride-sharing feeder service	Comparison of VTTS and operating costs	Statistical analysis; case studies with data from Federal Transit Admin., US Census Bureau, 2019	Pinellas County, USA (137,954 OD pairs); Marin County, USA (103,216 OD pairs); and Seattle, USA (103,216 OD pairs);	Deployment of a ride-sharing vehicle for last mile service made waiting time longer and cost higher. Unsubsidised feeder service costs exceed VTTS!
Jochem et al. (2021)	Smartphone multimodal traveller information systems;	Maximise individual travellers own utilities	N/A	Survey and multinomial logit model	Online survey using Survey-Monkey in Germany (732 people participated)	Smartphone mobility traveller information system (SMTIS) will influence mode choice decisions.
Militão and Tirachini (2021)	Shared Demand Responsive Transit (DRT) system with human operators vs. Autonomous Vehicles	Minimise fleet cost	Demand coverage; fleet size; capacity	Accessibility model	Munich, Germany: Mobilität in Deutschland – MiD Kurzreport (427 zones, 123,992 trips, 202,787 trip legs)	Autonomous Vehicles could reduce operational costs and increase customer utility.
Petruccelli and Racina (2021)	Feeder-trunk and direct-link schemes	Maximise individual travellers own utilities	Develop model to evaluate accessibility of transit system	Accessibility model	Matera Province, Italy (3,595,442 transport services)	The proposed model was valid in evaluating the accessibility of public transport.
Schlüter et al. (2021)	Autonomous Vehicles (AV) as DRT for rural to urban areas	Assess economic and environmental impacts	Travel time and capacity constraints for demand responsive transit	Activity-based simulation	Bremerhaven, Germany	Replacing motorised individual trips significantly decreases operational and environmental costs
Sörensen et al. (2021)	Demand Responsive Transit (DRT) scheme for rural areas	Assess potential for a fully flexible ride-pooling DRT	Actual operations	Spatial and temporal mobility analysis;	6-month pilot scheme of *Ecobus* in Oberharz, Germany	Main travel corridor and feeder-truck system setup identified

ger needs. The introduction of modular vehicles to feeder services can bring even more significant benefits to cost minimisation and service improvement in public transport systems. As feeder services have become more technology-oriented, new problems such as battery charging for electric feeder services (Chen, Hu et al., 2020) and transport information sharing (Jochem et al., 2021) have brought further challenges. A recent innovative application which utilises public transit as a backbone is a subsidised ride-sourcing service for feeders (Reck and Axhausen, 2020).

Twenty years ago, a survey on operational experiences with flexible transit services in USA (Koffman, 2004) drew only 24 responses from transit systems. Recently, there has been some assessment studies of demand-responsive feeder systems for specific cities, e.g. Atlanta (Edwards and Watkins, 2013), Canberra (Kilby and Robards, 2013). With data and computational costs reducing, customer expectations and budget pressures on public transport increasing, we expect more innovative flexible systems to be investigated, trialed and implemented in the future.

5.2. Bike Sharing

In many cities, people are encouraged to use bicycles as feeder services to be environmentally friendly. Shared bicycles have been around for a long time, starting with the free-to-use Witte Fietsen (White Bicycles) introduced in 1965 in Amsterdam. In the 1990, this has increased in popularity and spread to many cities, with docked bicycles that must be taken out and returned to particular locations. For example, Velib in Paris has over 20000 bikes in the system. In the last decade, this has exploded in China with dockless subscription systems. The functioning of these dockless systems relies on IoT technologies. At anytime and basically anywhere, service subscribers can use the smartphone app to locate a nearby available bike and “unlock” it for use. There is no need to return the bike to a prescribed location, but the user can use the app to “return” and pay for the bicycle rental anywhere when finished with it. Can these dockless bicycles be an essential part of an environmentally friendly feeder service for public transport?

Guo and He (2020, 2021) examined the data from Shenzhen of trips that end or started at a metro station, with a view to investigating the impact of the built environment on the use of these dockless bikes. They found that the trips that start from and end at a metro station respectively have peaks at the morning and evening rush-hours. Further, there is a one-hour lag between the trips that end at a metro station and those that start from a metro station. Since the commuting time on the metro is typically one-hour long, this is clear evidence that people actually use these bikes as a feeder service for commuting, both to access the public rail transit and to get to the workplace after getting off the train.

Through surveys, Guo and He also investigated which aspect of the built environment would encourage people to use this environmentally friendly mode of feeder service for commuting. They found that the main concern is accessibility: minimal effort to search for a bike, convenient place to leave them, safety and well-lit streets especially for the evening commute. The interesting factor is the number of bus stops. More bus and metro stops within easy walking distance discourages bike use; crowded feeder buses encourages bike use. Therefore, the layout of the built environment strongly impact the inducement of usage of different travel modes.

When dockless bikes were introduced in the mid 2010’s, over-expansion, over-capacity and lack of regulation led to many problems and subsequent re-organisation of the industry. Dockless bikes are better-managed nowadays thanks to the application of GPS and operational optimisations. Bikes are only allowed to be parked at designated locations otherwise users would be fined. Hired workers constantly move these bikes around to meet riders’ demand, rather than allowing bikes to float around.

Recent research on bike sharing have addressed bike demand forecasting and the bike rebalancing problem (BRP). Hua et al. (2020) used random forest to predict bike distributions based on journey data. BRP is a relatively new research area. The objective of such problems includes restoring bike quantities, meeting predicted demands, minimising the cost (or subjected to a cost constraint). Most of the existing research consider station-based systems, and address the static problem, where bicycles are moved during non-operational time (e.g. overnight). Methods include exact methods such as Branch-and-cut (Dell’Amico et al., 2014) and heuristic methods such as local search (Cruz et al., 2017). These algorithms typically take a few minutes to solve a real problem. For the dynamic rebalancing problem where bicycles are relocated during operational hours, Vogel et al. (2017) gave a mixed-integer programming model to find the optimal relocation and target fill-level at the stations, and Brinkmann et al. (2019) presented a stochastic-dynamic inventory routing model and applied approximate dynamic programming to derive a dynamic lookahead policy. The rebalancing problem for dockless bikes is more complicated because there are many more potential locations for the bikes. Pan et al. (2019) presented a very interesting deep reinforcement learning framework to **incentivise** *users* to pickup/return the bike at a different (nearby) location to achieve better overall re-balancing.

6. Responsiveness

Disruptions happen, demand shifts and are not deterministic. What we want for a smart public transport system is responsiveness and flexibility, where despatch and schedules can be adjusted dynamically in real time, ensuring that transport is available for people when they want and where they want, and they can get to their destinations on time.

With the wide availability of locational sensors and other data collection devices, and the increase in computational power, real-time disruption management is a real possibility. This is an active research area in recent years, with systems being developed for practical implementation. See, for example, Cormen et al, (2017), Dollevoet et al. (2017), Altazin et al. (2020), and Zhu and Goverde (2021).

Here we discuss a system developed and tested for Hong Kong Tramways, which is the oldest public transport system in Hong Kong, established in 1904 and still in use today. The system is a surface rail network serving the most congested part of the city. The trams do not run on dedicated tracks, and thus are often blocked by other on-road vehicles using the same space. Consequently, the trams have difficulty running to schedule. The only recourse is for the trams to be re-directed at the few terminal stations, for holding, short-turning or route-extension or alternative-route despatch. In the past, each inspector at each terminal station made such re-direction decisions separately, intuitively and subjectively, without any co-ordination and with no information on what was happening elsewhere in the network. By 2014, the company has laid RFID sensors along all the tracks of the tram system, so the position of every tram can be identified, and a forecast of the estimated times of arrival to the next station can be obtained in real time. Collaborating with The Chinese University of Hong Kong, a centralised system was developed to provide decision support for dynamic despatch and real-time response for disruption management. See Leung et al. (2016), Lai and Leung (2018). Using real-time and historical auto-sensed locational data, the system takes a “snapshot” of the current state of trams and motormen, and uses a mixed-integer optimisation model in a look-ahead rolling horizon framework, to evaluate the thousands of possible scenarios, to generate recommendations for the best combination of re-deployments of trams and motormen upon their next arrival to a terminal station. This enables a centralised decision-making at the Control Room instead of un-ordinated decisions at the various terminal stations. Extensive simulation studies have given a proof-of-concept that the centralised system provides enhancement of service and other performance metrics. The system leads to less overtime, less idle time, fewer violations of maximum working hours and higher service levels for this landmark heritage public transport service, thereby improving citizens' experience in their economic and recreational activities. The company is planning to incorporate real-time demand information (via smartphones, sensors) into the forecast and planning in the future. The use of real-time traveller data for disruption management has also been investigated by other researchers, e.g. van der Hurk, Kroon and Maróti (2018), Jevinger and Persson (2019).

As noted, the variability of on-road traffic is much higher than transit running on dedicated lanes or tracks; therefore, bus bunching is a frequently occurring phenomenon, and has been a long lasting problem in bus operations. The traditional regularity control measures aim to match the predefined bus headways by skipping stops or holding buses at designated stops, although such policies have been criticised for wasting bus capacity, leaving demands unfulfilled and unable to adapt to serious disruptions. The optimal control of buses operations has been much studied for decades; see, for example, Osuna and Newell (1972), Xuan, Argote and Daganzo (2011). Bartholdi and Eisenstein (2012) introduced and tested their novel idea of 'self-equalising headways' on a bus line in the city of Atlanta, USA, where drivers do not adhere to any specific schedule but hold for a duration proportional to the headway of the previous bus when they arrive at one of the two control points. Table 4 lists some recent research on 'self-equalising headways', all found them to have a self-rebalancing nature and are robust against strong bunching. Recently, with the sophisticated bus operation infrastructures, some scholars have studied the applicability of reinforcement learning (RL) approaches that holistically consider the impact to the entire system. With advances in data and computability, real-time control strategies can directly address the fulfilling of customer demands under disruption rather than the surrogate objective of merely equalising headways. In addition, bus regularity can be improved also by controlling the traffic lights to give differential bus priorities to buses with higher headways (See Hounsell and Shrestha, 2012).

Major disruptions, such as bus breakdown or track closures, are less frequent but can cause substantial consequences, leading to delay propagation in the whole system, and many passengers affected. For example, a bus breakdown at Singapore Changi Airport blocked over 30 buses for one hour (Land Transport Guru, 2021). Li, Mirchandani and Borenstein (2007, 2009) studied the problem of real-time bus service restoration by reassigning vehicles to interrupted bus trips (cut trips) caused by breakdowns, which they called the Vehicle Rescheduling Problem (VRSP). See Table 4 for some recent research on public transport re-scheduling due to disruption.

With bus breakdowns, companies often directly dispatched more buses to fulfil the demands of left-alone passengers. For rail transit, when the track renders the route unusable, additional trains do not help. Trans-modal substitute transport during a disruption event is necessary and is already used widely. Pender et al. (2013) found that, out of 71 metro service providers they interviewed, only one does not use substitute buses during an event of disruption. Kepaptsoglou and Karlaftis (2009) presented a methodological framework for the "bridging" of metro stations using bus services. Zeng, Durach and Fang (2012) investigated the use of taxis for disruption recovery service for the Munich tram system. Table 4 also list some recent research on bus bridging. The issue of contract design (between the metro provider and the substitute bus service) is also attracting research attention; see, for example, Zhang and Lo (2020). A dedicated review of bus bridging is given by Zhang et al. (2021).

Real-time disruption recovery requires instant solutions to handle large-scale instances promptly. Methods that take several minutes to solve is impractical, especially in a disruption event. In recent years, scholars are leveraging the advantages of machine learning and search-based optimisation algorithms to reduce the computational burden. Machine learning, including supervised and reinforcement learning can be used to accelerate Branch-and-Bound, by neural diving and neural branching to quickly derive feasible solutions. Reinforcement learning algorithms can also directly learn to optimise from a simulation environment. See Haydari and Yilmaz (2020) and Yan et al. (2021) for comprehensive reviews of machine learning for transport and logistics related problems.

In addition to recovery after disruptions, researchers have also investigated robustness and resilience in planning. To minimise the expected passenger travel time during disruptions, Naumann, Suhl and Kramkowski (2011) presented a stochastic programming approach for bus scheduling, and Jin et al. (2014) presented a two-stage stochastic model for an integrated metro-bus network. Dekker et al. (2021) discuss future directions in disruption management combining techniques from complexity science and operational research.

Table 4 summarises the recent research work related to disruption. There are two categories of articles. Planning articles are concerned with the optimisation of the network before a disruption occurs. Operational articles are concerned with what to do when a disruption occurs.

7. Technology

One area where the increased availability of data has had a major impact is passenger demand estimation and travel behaviour modelling. Decades ago, origin-destination trip data can only be obtained via household surveys. Because of the huge costs of surveys, there emerged a line of research since the 1970's in estimating the O-D matrix using indirect data such as traffic count on links or ticket counts at origin or destinations. These estimation methods include linear regression (Carey et al., 1981), linear programming (Sherali et al. 1994) and equilibrium-based approaches (Nguyen, 1977; Fisk and Boyce, 1983). With the widespread use of smartcards for fare collection nowadays, more precise information can be obtained (See, e.g. Wilson et al., 2009). Yet even now, inferences for the trip choices are still needed for systems that have entry-only or exit-only records, or systems with multiple O-D paths. See Hussain et al. (2021) for a review on the O-D matric estimation process using smartcard data.

Beyond simply O-D matrix estimation, Big Data and IoT nowadays can provide richer and more comprehensive information about public transport users. Passenger behaviour modelling describes the transport users' preferences under different circumstances, including trip purposes, start time, modal choice, frequency and duration. Quantitatively describing their behaviours is the fundamental step toward improving passengers' utilities and the cost-effectiveness of the public transport system (Bagchi & White, 2005). For example, commuting passengers may prefer a faster route, while a recreational traveller would choose a less crowded path.

Acquiring travellers' trip purposes requires travel surveys traditionally. Bagchi & White (2005) stressed that the insufficiency of survey data had limited relevant research in trip purpose inference in earlier years. Over the past 40 years, automated fare collection and passenger count systems have come into use. 1972, the Bay Area Rapid Transit System (BART) introduced a magnetic-strip card

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Table 4
Recent research on Disruption Management (since 2017).

Authors (Year)	Application	Objectives	Constraints	Methodologies	Data	Key Results
Bus Bunching						
Zhang and Lo (2018)	Self-equalising headway control	Minimize headway variance	Closed loop routes; no overtaking; single control point;	Two-way-looking dynamic control	Artificial data (6 buses)	Proposed method greatly reduce headway variance in stochastic and deterministic scenarios.
Alesiani & Gkiotsalitis (2018)	Holistic bus-holding	Minimise deviation from planned headways and excessive trip times	Circular bus line; no overtaking; holding at intermediate time points allowed	Reinforcement Learning (Deep Q-learning)	A bus line in Singapore (22 bus stops; 220 trips)	Proposed method has superior stability and lower variation vs. traditional headway-based holding.
Liang et al. (2019)	Bus holding and stop skipping	Equalise headways	Circular bus route; single control point; consider waiting passengers	Rule based dynamic control + simulation	Artificial circular route (10 buses); Route 80 in Changchun, China (20 bus stops)	The method improved service levels, resisted bus bunching, and regulated bus headways.
Wang and Sun (2020)	Bus withholding	Equalise headways	No overtaking	Reinforcement Learning (Multi-agent Proximal Policy Optimisation)	Artificial data (6 stops; 12 buses; 10 passengers / stop)	The Reinforcement Learning agent could automatically learn to hold for equalising headways.
Vehicle/Schedule re-optimisation						
Lusby et al. (2017)	Railway rolling stock re-scheduling	Minimise cancellations, seat shortage, mileage and decoupling	Fleet capacity; unit location; depot capacity;	Branch & Price; path formulation	DSB S-tog, Copenhagen Denmark (up to 28719 stops; 1086 trips; 3259 subtrips)	Model could be used for disruption management and tactical level planning.
Dollevoet et al. (2017)	Iterative re-scheduling of timetable, rolling stock and crew	Minimise delays, deviations from planned turns, shuntings, and duties	Infrastructure; rolling stock and crew constraints	Mixed Integer Programming, Lagrangean Relaxation, set covering heuristic	Dutch railway data (116 departed trains)	This framework could produce new timetable and rolling stock and crew schedules in short time for track blockage.
van Lieshout et al. (2018)	Rescheduling buses and crews	Minimise delay, reassignment and cancellation costs	Crew and vehicle constraints	Lagrangean Relaxation	Artificial data generated as in Li et al. (2009) (700 trips)	The method could effectively reduce delay and cancellations in disruptions.
Guedes and Borenstein (2018)	Multi-depot Vehicle Rescheduling Problem	Minimise operational costs and changes in offline scheduling	Peak demand; vehicle and crew constraints	Column Generation	Bus transit in Santa Maria, Brazil (20 lines; 9 stations; 529 daily trips; 171 routes)	The method was efficient and robust, and could solve problems with up to 2500 trips (Data from Guedes and Borenstein, 2015).
Ortega, Pozo and Puerto (2018)	Reduced fleet rescheduling	Minimise deviation from initial timetable	Vehicle and crew constraints	Mixed Integer Programming; reformulation solved by MIP Express 7.7	Train line C4 of Madrid, Spain (7 stations), demand survey data *from* Mesa et al., 2009; 2013)	This method could efficiently reschedule online.
Malucelli and Tresoldi (2019)	Vehicle and Crew Rescheduling	Minimise services not covered, extra working time, and change in driver duties	Vehicle and crew constraints	Column Generation;	Milan (Italy) ATM tram line 14 (104 stops; 25 vehicles; 66 drivers; 16 relief points) and trolley bus line 92 (66 stops; 20 vehicles; 50 drivers; 5 relief points)	This method could efficiently reschedule with good service regularity.
Zhu and Goverde (2021)	Rescheduling for multiple connected disruptions	Minimise delays and cancelled trains	Train and crew constraints; no train entering disrupted regions	Mixed Integer Linear Programme solved by Gurobi	Dutch railway network (38 stations; 10 train lines)	The proposed method could solve multiple-disruption problems.
Bus Bridging						
Jin, Teo and Odoni (2016)	Bus bridging route design and bus allocation	Minimise commuter travel delay	Bus and crew constraints	Column Generation; path-based multicommodity flow; optimisation-based procedure	Major city transit network ((i) 109 stations; 236 directed links; 4 lines; 3 routes; 20 buses; and (ii) 7 stations; 4 lines; 4 routes; 35 buses)	The proposed method could solve bus bridging problems efficiently

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Table 4 (*continued*)

Authors (Year)	Application	Objectives	Constraints	Methodologies	Data	Key Results
Gu et al. (2018)	Flexible bus bridge routes	Minimise bridging time and passenger delay	Bus and crew constraints	Weighted shortest processing time first rule	Metro Line 9, Songjiang District, Shanghai (6 stations; 6 depots; 55 buses)	The proposed method could solve bus bridging problems in metro disruption efficiently.
Itani, Srikukenthiran and Shalaby (2021)	Capacity-constrained bus bridging with shuttle bus and route allocation	Minimise overall subway and bus rider delays	Bus and crew constraints; bus bay capacity	Genetic Algorithm	Four subway lines of TCC Toronto, Ontario (146 bus routes; 1926 buses; 249 street cars and 868 trains)	The proposed method could provide major time savings to passenger during a bus bridging event.
Chen and An, 2021	Bus bridging routing and timetabling for rail disruptions	Minimise total passenger delay	Bus and crew constraints	Search-based heuristic	Caulfield-Dandenong of Cranbourne line in Melbourne (13 stations; 80 buses, each with a capacity of 80)	The proposed model could jointly optimise the bus bridging routes and time bridging strategy with multiple routes.
Bojic et al. (2021)	Bridging plan using heterogeneous fleet	Minimise travel delay and maximise passengers served	Bus and crew constraints	Mixed Integer Programming solved by CPLEX; simulation	MRT and bus lines in Singapore (4 stations; 3 bus lines) and smart card data (6000 passengers)	The proposed method could optimise bus bridging plan with different passenger priorities.
Robust scheduling and planning						
Wu et al. (2016)	Integrated timetabling planning and delay control	Minimise tardiness, missed connections, and control cost	Safety control margin within a threshold	Stochastic Mixed Integer Programming	Artificial networks ((i) 2 transfer nodes; 3 bus lines, (ii) 3 transfer nodes, 3 bus lines)	The proposed method provided a framework to evaluate safety control margin.
Zhao, Jin and Lee (2017)	Personal Rapid Transit network design	Minimise expected travel cost and construction cost	Budget; demand; flow conservation	Two-stage stochastic programming	Sengkang LRT in Singapore (4 lines; 12 stations; 132 OD pairs)	The method could plan a personal rapid transit network under stochasticity.
Yap et al. (2018)	Quantification of link vulnerability in multi-level network	Minimise societal costs pf a disturbance	Capacity constraints	Pre-selection criteria; simulation	Randstad Zuidvleugel, Netherlands (5791 zones)	The method could identify vulnerable links in the network.
Gkiotsalitis et al. (2019)	Bus allocation with interlining and short turning	Minimise passenger waiting cost and operational cost	Passenger waiting time; fleet size; budget	Genetic Algorithm	Bus network in Hague, Netherlands (8 bus lines; 220 buses)	Proposed method maximises operational efficiency by short turning and interlining
Tang, Lin and He (2019)	Dynamic Electric Bus scheduling	Minimise operations costs (vehicle fixed and recharging)	Original timetable; battery capacity; vehicle recharging plan	Buffer-distance strategy; Branch & Price	Bus lines in Beijing (6 routes; 39 – 96 trips)	Model could dynamically fulfil schedule requirements and recharge vehicles.
Ying, Chow and Chin (2020)	Train scheduling with limited rolling stock	Minimise journey time, Reduce energy consumption,	Rolling stock limit; Headways, run & dwell times; safety margin	Deep Reinforcement Learning (Actor Critic)	London Victoria Line (15 stations; 24 trains)	The proposed method was better than heuristics. It was efficient and robust.
Cats and Krishnakumari (2020)	Network structure and Performance, Robustness	Measure functional capacity, connectivity, and induced impedance	Assess connectedness and robustness under different failure scenarios	Complex network theory	Rail networks in Shanghai (China), the Randstad (Netherlands), and London (UK)	The Randstad is found to be the least robust network.

for automated fare collection. In 1993, New York introduced a prepaid metro card. In recent years, with the increasing popularity of pay-as-you-go cards, there is abundant traveller information where their purposes can be inferred. Trip purposes are either derived by rule-based methods (Alsger et al., 2019; Devillaine et al., 2012) or by learning methods (Kusakabe and Asakura, 2014; Lee and Hickman, 2014; Ma et al., 2017). Rule-based methods rely on experts' knowledge to handcraft a set of classification criteria based on the user's spatial-temporal and frequency information. In comparison, learning methods rely on the combination of socio-economic data, trip purpose survey data and smart card data as the training dataset. The mainstream methods include naive Bayesian and decision trees. Alsger et al. (2019), Kusakabe et al. (2014), and Ma et al. (2017) respectively claimed accuracies of 92%, 86.2%, and 94.1%. Other interesting research have been conducted, such as how the weather would affect traveller's behaviour (Arana et al., 2014) and the identification of extreme behaviours (Long et al., 2016). Wang et al. (2015) combined the smart card data of one working day in Beijing and the price elasticities based on travellers' surveys to determine the reasonable fares to maximise utilities.

We remark that we can barely find any information on computational efficiency (CPU brand and computation duration). We infer that the algorithms mentioned above are relatively computationally light. In the age of automated data collection, unbiased manual survey data remains very scarce. Information on social media also exhibits bias. The major constraint is data quality and sufficiency since relevant research relies on both smart card data and survey data.

With the rapid advances and proliferation of new technologies, we can now design and implement smart public transit systems. Big advances have been made in information technologies, where we now have ubiquitous sensors to know where the buses are and where the customers are, for better planning and real-time operational adjustments. Berlingerio et al. (2013) and Lee and Nair (2021) describe the use of mobile phone data for transit planning in Abidjian, Côte d'Ivorie. We now also have many communication channels where information can be provided to the passengers, because people feel a lot better when they know, and they can better evaluate alternative options. There are now many, many travel planning apps available, e.g. Googlemaps, Citymapper, Moovit. These map-based apps will show the route from origin to destination for various mode choices (driving, public transit, walking). These apps are getting more sophisticated and information-rich, such as indicating transfer points, walking distance, traffic conditions, etc., even occupancy percentage of the trains/buses, so passengers can make an informed choice. See Horn (2004) for one of the first journey planners that combined both fixed and on-demand public transport modes. Recent research has shown that routing advice that accounts for stochasticity significantly improves the probability of passengers arriving on time and their satisfaction, particularly when disruptions occur. See, for example, Bérczi et al. (2017), Leng and Cormen (2020). In addition to multimodal itineraries, travellers also expect these planning apps to consider individual preferences, which creates additional computational burden. Horstmannshoff and Ehmke (2020) recently proposed a solution sampling approach. How to enable real-time customised recommendations for all travellers is an ongoing active research area.

Technology can also help to improve journey comfort for passengers, by providing real-time information on transit crowdedness. Passengers' experience in using public transit can be attributed to various factors such as total journey time, reliability of the transit service, number of transfers, walking distance, and instructions and guides provided by the operator. An important aspect of passengers' experience is their perception of the service during the journey, influenced by the interactions with the transit operator and other passengers and the environment of the transit infrastructure. Transit crowdedness is one of these critical factors that affect passengers' perception of the transit service. For example, Google (2021) and Moovit (2021) estimate transit crowdedness by using crowdsourcing and make such real-time information available to the public. Such information enables not only passengers to make informed decisions to plan for their trips, but also transit operators to dynamically despatch their vehicles or trains to reduce crowdedness for better passenger experience.

The challenge for service providers and researchers are issues regarding rapid updating, "clean" and accurate information, data sharing and privacy. As more data becomes available from multiple sources, the consolidation and reconciliation of the information may also become an issue. Zannat and Choudhary (2019) pointed out that the challenge of using Big Data for public transport planning include data gaps (discontinuity and missing location info), data extraction (elicitation of trip purpose from social media data) and data integration (linkage of social-demographic info to itineraries). Real-time planning algorithms have to resist "nervousness" caused by rapidly changing data input. In terms of dissemination to the public, conciseness and readability of the information must be considered so that passengers are not overwhelmed by information-overload.

8. Post-pandemic Public Transport

As we have all experienced during the Covid-19 pandemic, when cities went into lockdown, the ridership of the public transport system dropped sharply. In many other aspects, our lives have changed drastically in this past year. Shops are opening with reduced hours, work and schooling are done at home, with meetings held online. International travel has been reduced by over ninety percent in many countries. Hopefully, the pandemic will pass, but maybe our lives will be changed and we will not go back to exactly the way it was.

While many industries and businesses are suffering, one industry that is doing well is the home delivery service. Online retail sales grew by 22% in 2020. Increase in online ordering generated by Covid19 pushed online retail sales as a percentage of the overall retail sales to 25.9% in Korea; this percentage also doubled in Singapore, from 5.9% in 2019 to 11.7% in 2020 (UNCTAD, 2021). In the future, perhaps not only goods but also services will be done by home delivery? One home-delivery service industry that has been on-going even before the pandemic is the home health-care service (Nasir et al., 2019). Home health-care means not just nurses visiting homes, but also delivery of medicines, and pickup of samples for tests. These have to be done at certain time windows (when patients are available or at meal times), and subject to precedence constraints. The nurses have specialised skills so one does not want them to drive heavy good vehicles to deliver equipment or meals. The visits to the patients have to be co-ordinated, with the equipment and the nurses being at the same location for the treatment to be administered. Nasir and Kuo (2020) have shown that if we separate the delivery of meals and medication from nursing care trips, as long as we meet the precedence requirements, then asynchronous trips allow more trips to be made and take care of more patients, leading to better utilisation of valuable resources (nurses, specialised vehicles and equipment). Might home delivery be the future of service industries? Would work patterns also change, so we do not commute to our offices in the central business districts anymore, but meet variously "at home" or in satellite offices. What are the implications for public transport? Gkiotsalitis and Cats (2021) discuss some adaptations in planning and new research directions arising due to the Covid19 pandemic.

9. Other Emerging Trends and Technologies

Three emerging technologies have generated a lot of recent research. Here we briefly disucss their impact on public transport systems.

- *Electric vehicles* – The current challenge is the limited range and the location of the charging stations, which add a lot of complexity to the design and planning of public transit systems. See, for example, Olsen, Kliewer and Wolbeck (2020), Yıldırım and Yıldız, (2021). With technology improving, some aspects of the problem might go away. If the delivery items or demand capacity is so small that the trip is finished before the battery runs out, then recharging is not a concern. The complexities due to this technology might change in the future.
- *Autonomous vehicles* – In 2011, a 3 million pounds personal transit network called ULTra starts its service at London Heathrow Airport with 21 automated vehicles, Each automated vehicle is an unmanned pod running on dedicated guideways. Passengers travelling between the terminal and the car parks can readily access by pressing a button. These personal pods are all battery-powered and automatically charged at dedicated charging points. This technology is widely proposed and adopted in other airport around the world, such as Chengdu Tianfu Airport in China and Jewar International Airport in India. Unmanned micro-transit service also has a great potential in urban settings. As summarised by Shaheen et al. (2020), it has the advantages of being flexible and demand-responsive because it can react to passengers' requests and deviate from its original routes. It is still under-deployed due to technological barriers. A current limitation of autonomous vehicle technology is the requirement of dedicated lanes, and the vehicles cannot venture out to mix with general traffic. There is much active research on improving navigation of autonomous vehicles in mixed traffic environments. See, for example, Chen et al. (2021), Prédhumeau et al. (2021). As technology improves, then the challenge might be the integration of the use of these vehicles into a flexible on-demand public transport service. Eppenberger and Richter (2021) studied how shared autonomous vehicles can improve accessibility and social equity.
- *Ride-sharing* – A traditional shared-ride service is the Dial-A-Ride paratransit service for the disabled and elderly which has been in use and studied for many years. See Ho et al. (2018) for a survey of the models and methodologies for Dial-A-Ride problem (DARP). We only note here that recent research have addressed operational efficiency and service issues by considering DARPs with transfers between vehicles, and stochastic models for route deviations to accommodate late requests. See Cortes et al. (2010), Bouros et al. (2011), Masson et al. (2013) and Bruni et al. (2014).

  Certainly, ride-sharing services will be an important aspect for public transport, particularly in terms of flexible on-demand feeder services, especially for rural areas. See, for example, Elting and Ehmke (2021). The modus operandi for these new shared-ride services are also different, with the ride-sharing company acting as a platform that links a multitude of service providers and customers. Ma et al. (2015) described a mobile-cloud architecture that matches new shared-ride requests with nearby taxis with on-board passengers. The increasing popularity of ride-sharing will impact public transport on several levels. At the strategic level, ride-sharing must be considered as a transport mode along with buses and rail, and the overall planning must be done in an integrated fashion (See, for example, Steiner and Irnich, 2020). Operationally, since the offer of rides is not centrally controlled, the matching of supply to demand requires different mechanisms compared to traditional transit modes (See, for example, Haferkamp and Ehmke, 2021). Lastly, increasing use of ride-sharing may have other impacts, such as traffic congestion, private car ownership, etc. See Diao, Kong and Zhao (2021). Shared mobility is a broader concept that may involve hybrid modes of public and private transport. It includes bike sharing, car sharing, car pooling and micro transit. Enzi et al. (2021) and Enzi et al. (2021) describe a car- and ride-sharing system for a corporate fleet where uncovered requests are assigned to other (public) transport modes. As another example of the sharing economy, Gansterer et al. (2021) discusses a shared package delivery operation where pickup-delivery requests are exchanged and re-assigned among the collaborating carriers. See Mourad et al. (2019) and Shaheen et al. (2020) for surveys of models, algorithms and strategies for shared mobility.

  All these emerging trends and technologies indicate that public transport is becoming more customised towards the needs of the people. The goal is no longer moving passengers from origin to destination, but supporting people's activities. Integrating with urban planning concepts, some cities have also experimented with the concept of 'shared road space' for mixed use by pedestrians, cyclists and vehicles. In 2012, guard-rails and elevated pedestrian walkways were removed in Exhibition Road in London such that the road surface is not differentiated by user types. This scheme has been implemented in many other cities. The impact of this and other traffic-calming measures are evaluated by various studies, such as Kaparias et al. (2016) and Gonzalo-Orden et al. (2018).

10. Challenges for the Future

With the increase in computational power and data availability, the models and methods for the design, operation and management of public transport systems have been greatly advanced, from simplified partial models solved by heuristics, to integrated models solved by exact methods, to more comprehensive realistic models with robust solutions that accounts for uncertainty. For a smart city, richer and more precise information will be available to enable planners to devise and operate public transport systems that better meet the needs of the travellers. In addition, the ubiquity of data and IoT technologies has also enabled new demand-responsive public transport services, and innovative modes of public-private shared mobility (e.g. ride-, bike- and car-sharing).

This may impact future directions in public transport research. Firstly, within the traditional planning framework, the trend is for more holistic and integrated models that incorporate more service quality considerations and anticipate uncertainty. This will lead to more research on solution approaches for large-scale stochastic programming, multi-objective programming, and robust optimisation. Secondly, to support the operation of real-time demand-responsive (and demand anticipative) public transport, fast algorithms are needed to determine vehicle re-routing and or holding, customer request acceptance and assignment, etc. This will lead to research on fast algorithms for real-time dynamic decision models, and analyses on their effectiveness.

With lockdown and flexible work hours, our work patterns might change, our living patterns might change, and our lives might change. In the future, maybe commuting and rush-hour traffic will no longer exist? That might be good news for public transport planners, because managing the rush-hour peak and off-hours with cost-effective service has always been a challenge. With changing work patterns and work locations, maybe there is no more CBDs for cities, thus public transport will not be designed as hub-and-spoke systems but much more complex, nor are there needs for feeder services. When instead of customers coming to the shops, we are bringing services to the customer, what are the implications for public transport? Demand patterns may be changed in both location and time. For the future, we may no longer be thinking about mass transit but more towards on-demand services (and definitely multi-modal transport systems). How to manage a multi-model system that provides good service in a cost-effective way will be a challenge.

In fact, the trend is towards *personalised passenger journeys.* The most important element in a public transport system is the passengers, who are the ultimate receivers of the services. The public transit services of a smart city must be passenger centric. Public transit operators and their technology partners have been devoting great efforts in offering more personalised journeys to passengers. For example, Axon Vibe (2021) analyses users' commuting behaviour from locational data, provides the users with personalised transit recommendations, and helps transit operators to deliver personalised messages to passengers. Big data analytics and real-time multi-modal trip planning are the essential technology drivers for personalised passenger journeys.

Another major development is the concept of share mobility, which has engendered new services such as ride-sharing, bike-sharing, car-pooling, car-sharing, etc. A significant difference for these shared mobility modes is that they are not centrally controlled, but involve different stakeholders with different incentives. Research studies on these systems may involve bilevel programming and game theory in addition to tradition optimisation approaches.

In the future, a traveller's journey will likely combine different modes of transport in a hybrid public-private system. The concept of public transport should be expanded to consider not only the movement from origin to destination, but how best to support the purpose of the activity of the "passenger". The smart public transport systems of the future will have to be flexible, responsive, offering quality customised service. Definitely, the complexity in planning, coordination and management will increase. In this paper, we have raised some issues relating to the goals that public transport for a smart city should have, and some emerging trends for transitioning to the future. Definitely, the customer will demand higher service levels. Definitely, public transport systems will change increasingly from mass transit to on-demand services. This will surely lead to increased complexity in planning, in coordination and in disruption management in real time. This is good news for us operations researchers, because there will be many, many more interesting problems and exciting research topics for all of us to explore!

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Supplementary materials

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