

Spectrum of Public Transit Operations: From Fixed Route to Microtransit

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Spectrum of Public Transit Operations: from Fixed Route to

Microtransit

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Linked Open Data

Simulation code used for Case Study: https://github.com/BUILTNYU/FTA_TransitSystems

Generated Use Case Study Data Set: <https://doi.org/10.5281/zenodo.3672151>

Executive Summary

There is an increasing concern about the need to improve public transit operations in response to the rapid urban growth, transportation trends and social changes in cities. To assist the transit planners responsible for vehicle operations and planning, this report summarizes the decision-making process involving the selection of the most appropriate design and technology for public transit operations. Based on the findings and observations from a review of the relevant literature and the information gathered from practical challenges from real world deployment of emerging technologies, this compendium provides a broad overview for public transit design to facilitate the planning process by transit authorities at strategic, tactical, and operational levels. Building upon the knowledge gained from state-of-the-art-methods for fixed and demand responsive systems, this work contributes to a better understanding of the approaches needed to address challenges encountered in the successful implementation of public transit operations, particularly in regard to more flexible, real-time operations like microtransit.

For regions with high transportation demand, the conventional ‘fixed route’ transit service is the most favorable due to a high degree of resource sharing. The operation planning of the fixed route transit service involves line planning, tactical planning, transfer penalties, and transit technology selection. The line planning problem in transit network design deals with determining the structure and service of the network. Although simple structures can be used for line planning, researchers have evaluated various different line structures including direct lines, exclusive lines, hub-and-spoke, feeder trunk, and custom designs including new models for real-time mass transport network optimization as well as for line planning and allocation considering competing mobility actors. Tactical planning for fixed route transit service involves setting the service pattern of each line by determining frequencies, locating stops, and developing timetables for the service. Approaches to optimizing frequencies vary from analytical models and mathematical programs to optimization methods combining frequency with other factors such as route setting and vehicle capacities. Frequency setting is a key determinant in solving the stop-spacing and optimal stops problem in transit network design. The times at which a vehicle will service each stop, i.e. the timetabling of the transit system, serves as an input to the vehicle scheduling and crew scheduling process. While vehicle scheduling assigns the fleet to the timetables, drivers and other staff are assigned to the fleet operations in crew scheduling. In the real world, the network of fixed route transit lines faces many complications in their regular service and structure; this mainly consists of bus bunching, headway control, and imbalance

between vehicle capacity and demand. Techniques to combat such issues include alternate deadheading, careful schedule coordination, optimal service patterns such as short turning pattern, zone scheduling, and limited-stop schedules. With the availability of real-time location information, these problems are better addressed using real-time control strategies especially issues like bus bunching, headway control, transfer penalties and transfer synchronization. The selection of transit technology is a complex decision process in transit system planning; various analytical models including experiences from other agencies can be used to compare and match the requirements of the system for resolving the problem of selecting the appropriate vehicle technology and size.

The traditional fixed route transit service, however, results in higher cost in regions with sparsely distributed demand. For this reason, the mass transit evolved to provide some degree of flexibility by offering 'flexible route' transit service. Although the service ranges from fully customized to flexible route, its major variations consist of demand response transportation, flex-route or deviated fixed-route and first-mile last-mile shuttles. In addition, there are various hybrid services proposed by researchers that combine fixed route and demand responsive services. The planning process for flexible route transit services can be broadly classified into two categories: one is strategic planning and operations which includes strategies to choose the best service type between fixed and flexible route and the other is performance evaluation that consists of measures to evaluate efficiency and feasibility of flexible route transit system.

The most flexible form of microtransit is the 'door-to-door' on-demand service. Although this serves as a solution to the last mile problem in transit as feeder service, various alternative structures of on-demand door to door transit service have been explored in recent years. This compendium integrates the design and evaluation of such services using current knowledge, provides design lessons using information from real world practices across different cities and discusses future scenarios to guide the transit planners in choosing the appropriate transit design and policies.

The underlying objective of providing improved public transit service is to improve the mobility and accessibility of the public. While there has been an increased interest in development of flexible route transit services, there are various challenges that need to be addressed for real world implementation of such services. This compendium broadly classifies the key challenges as technology, infrastructure, market dynamics, and governance. With the advent of intelligent transportation systems (ITS) and emerging technologies, not only the commuters are favored from the real-time location information, but the transit planners also

benefit from the data availability. With advanced technologies, users' data, systems data, and a wide range of open-source tools the performance of flexible transit services can be effectively improved. It is necessary to ensure that the transit service efficiently integrates with other mobility services operating in the same environment; the planning for interaction of transit system with the urban environment constitute the infrastructure challenge. Some of these issues can be addressed by improving speed, reducing information barriers, limiting stops and reducing discharge flows for underutilized vehicles, adopting flexible road space allocation strategies, and evaluating trade-offs between demand and capacity. While quality of service and fare are major factors driving the transit ridership, social impacts and equity issues need to be considered for evaluating market dynamics. The institutional barriers, on the other hand, are essentially the regulations, policies, and funding issues. For successful implementation of flexible transit service, it is important to consider the dynamics of the emerging mobility services especially MaaS (Mobility-as-a-Service) and the governance attributes associated with the potential combination of transportation services to ensure an efficient and equitable transport network.

To make the methods surveyed in this compendium more accessible to readers, a case study is created to demonstrate their usage. A simulation-based evaluation tool is presented that models the three major classes of transit operations i.e., fixed route, flexible route, and on-demand transit services. These design methods are implemented on an existing bus route service that runs in Brooklyn, New York City using a common dataset and the simulation tool (both made publicly available for readers). The simulation framework extends current state-of-the-art methods to provide necessary support for comparing different design strategies and evaluating system performances. The inputs used in the case study can be easily modified to compare different design scenarios in any setup using the simulation tool.

The study concludes with several recommendations made along the dimensions of technology, infrastructure, market dynamics, and governance. Within these dimensions, we recommend the following key next steps for the U.S. DOT and agency practitioners:

- U.S. DOT should create a new certification process for transportation technologies and policies in which they are evaluated in a common repository of publicly accessible simulation scenarios constructed for a range of different cities. This will allow technologies to be commonly tested and to output common performance measures, resulting in certifications for different improvements (like increasing accessibility, shifting travelers from cars, being supportive of seniors, etc.), across different cities. The repository should

include tags for the regulations in place in those cities so that over time, governance impacts can be measured.

- For road space usage, U.S. DOT should create a curb management benefits database similar to the ITS benefits database. This database will host case studies and common performance metrics of different operations so that such data becomes available for learning about different curb management strategies.
- U.S. DOT should initiate a large scale data collection effort with a community where multimodal trips are made, perhaps using a Mobility-as-a-Service (MaaS) platform or smartphone survey tool, to create a publicly available data set of multimodal travel (for which we currently do not have). This data will help better understand the demand for multimodal trips, the operators' incentives to provide such trips, and ultimately how they should work together in a common MaaS market.
- Lastly, this compendium points to the need for a knowledge base in the U.S. for demand-responsive transit operations. While there are centers that cover shared use mobility and transit, they tend to focus on policy. There needs to be an institution for the study of the spectrum of transit operations from fixed route to microtransit, and all their related impacts.

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Section 1: Introduction

1.1. Project Background

Public transport, or mass transit, is a public service that pools travelers' trips together to achieve economies of density and spatial scope (Jara-Díaz and Basso, 2003). Its goal is to provide quality, affordable mobility to users as a public good (Desaulniers and Hickman, 2007). But what constitutes an appropriate service for a city or region? This question has remained difficult to address due to the myriad of scenarios and needs from different communities and will only become more consequential with increasing urbanization (UN, 2018) and population increase (UN, 2017).

Meanwhile, the solutions available to policymakers have also become more complex with the emergence of new mobility services due to innovations in information and communications technologies (ICTs) and the Internet of Things (IoT) (see Chow, 2018). What might once have “simply” involved a decision of whether to invest in a light rail line or a bus route with some flexible stops may now also include considerations of bikeshare, microtransit feeder services, or taxis, all compounded by considerations of automation and electrification (WEF, 2019), and whether to operate as public fleets or outsourced to private mobility providers. **Figure 1.1** illustrates the contrast in services available to travelers in two cities in the U.S.: Arlington, TX, and New York City (NYC), NY. **Figure 1.1(a)** shows the service coverage area provided by Via and **Figure 1.1(b)** shows a snapshot of all public transit vehicles (NYCT trains, buses, Skytrain, LIRR, PATH, among others) operating at 2:25PM on January 23, 2020.

As a result of these disruptive technologies, mobility companies have emerged to take advantage of the opportunities available to them. The types of options fall within a “Mobility-as-a-Service” (MaaS) system where travel is not a modal system but a conglomeration of options, often managed through a unified gateway or platform, to support travelers (Hensher, 2017). The range of potential options in this MaaS paradigm is shown in **Figure 1.2**.

Despite the interest in these technologies, the success of deployments has varied. Several microtransit providers have shut down in recent years; examples include Bridj (Woodward et al., 2017) and Ford Chariot (Korosec, 2019a). Due to these operational challenges, public agencies like the Federal Transit Administration (FTA) have sought to encourage more pilots and research through programs like the Mobility-on-Demand (MOD) Sandbox Program, with a number of projects highlighted in **Figure 1.3**, mostly dealing with first- and last-mile access.

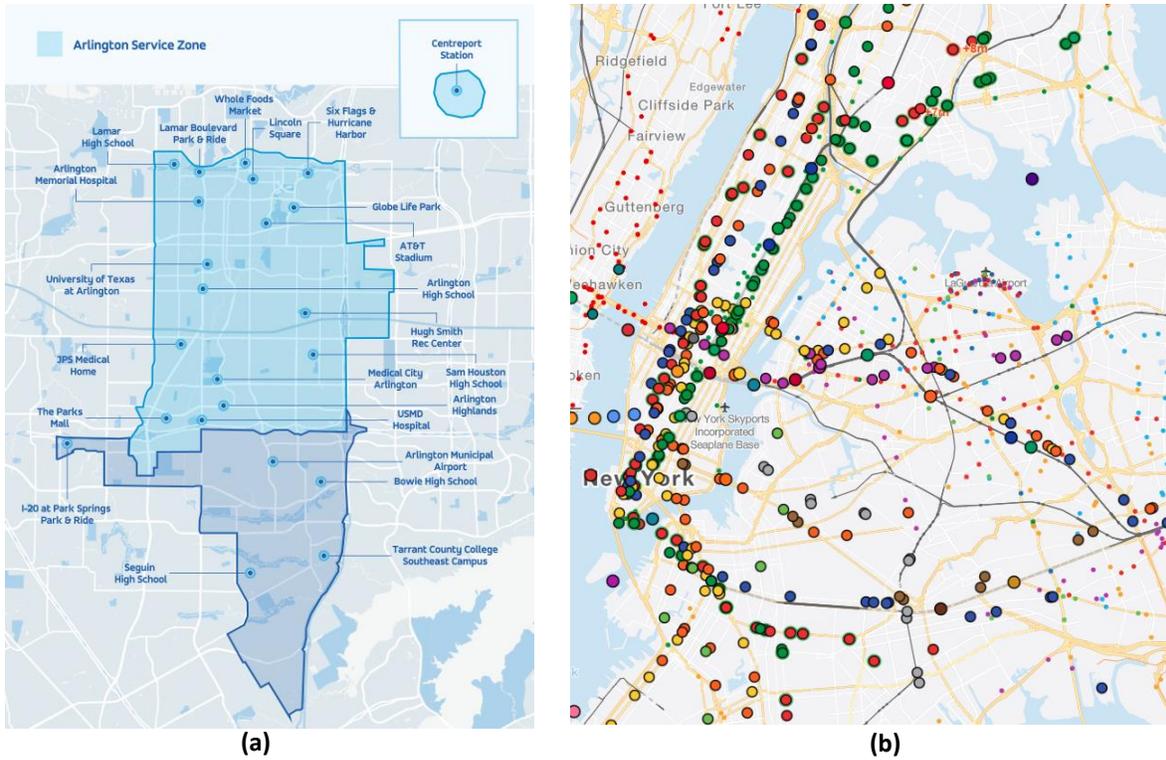


Figure 1.1. Comparison of transit services in (a) Arlington TX provided by Via (source: Via, 2019), and (b) New York City transit (source: TRAVIC, 2020).

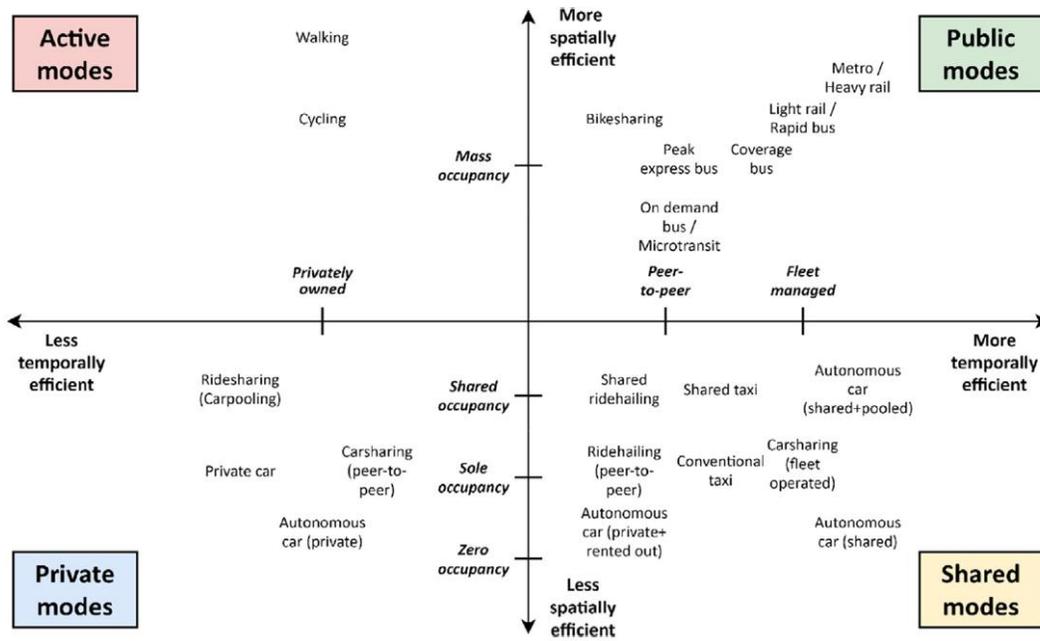


Figure 1.2. Different modes from Mobility-as-a-Service (source: Wong et al., 2019).

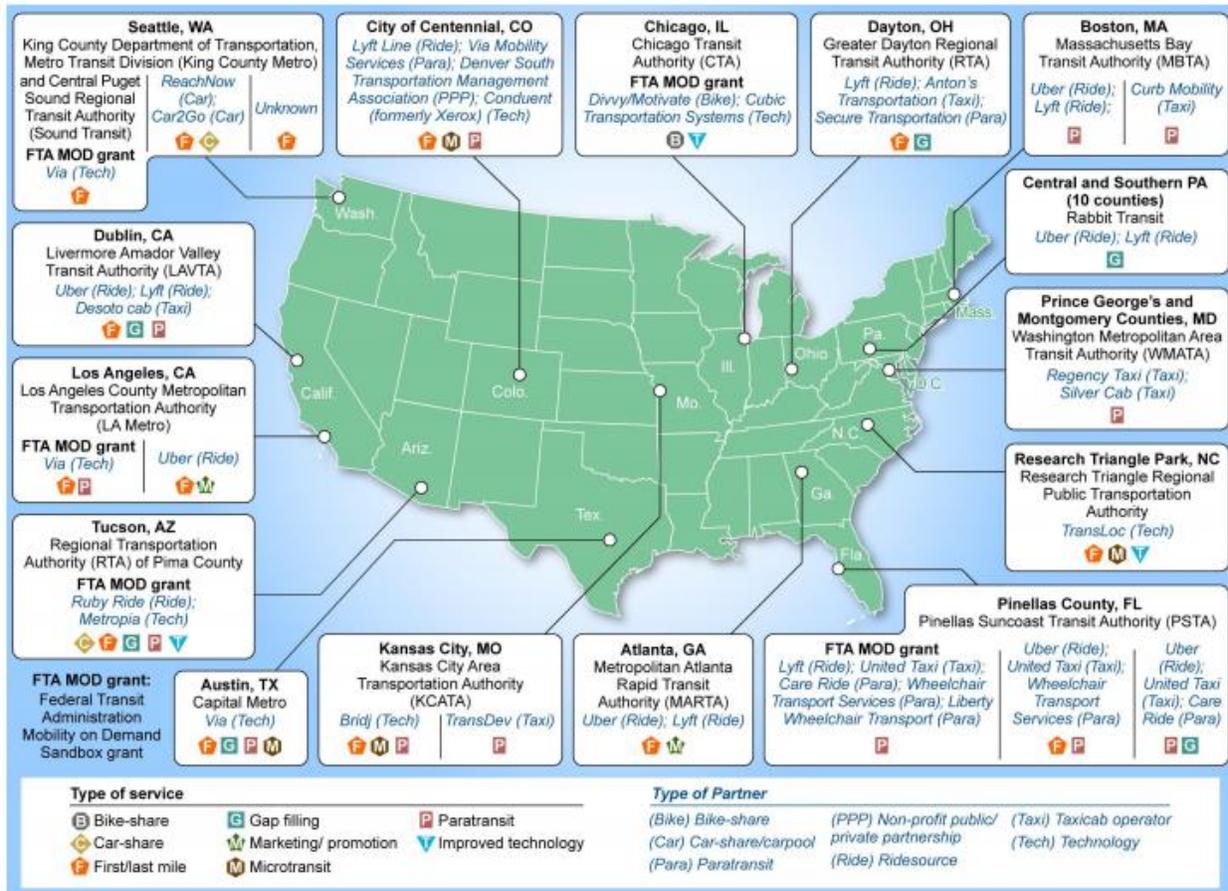


Figure 1.3. Selected transit partnerships, several of which are from the MOD Sandbox program (source: GAO, 2018).

Clearly, the industry has a need to better understand the spectrum of transit operations, which can range from full fixed route services, through flexible services, to fully MOD services serving passengers door-to-door or virtual stop to virtual stop (Hazan et al., 2019). While there is an abundant new literature on these operations, there is also a long history to research in these areas, many of which preceded the advances in ICT needed to make Demand Responsive Transit (DRT) feasible.¹ For example, **Figure 1.4** illustrates research in the late 1970s comparing the efficiency of conventional fixed route service to dial-a-ride services which involve door-to-door service with reservations made 24 hours in advance. The figure shows the existence of a

¹ MOD deals with a broader array of mobility services beyond “transit” which involves the act of a server transporting passengers; examples of non-transit MOD include carshare.

demand density threshold over which fixed route service operates better than DRT, and vice versa.

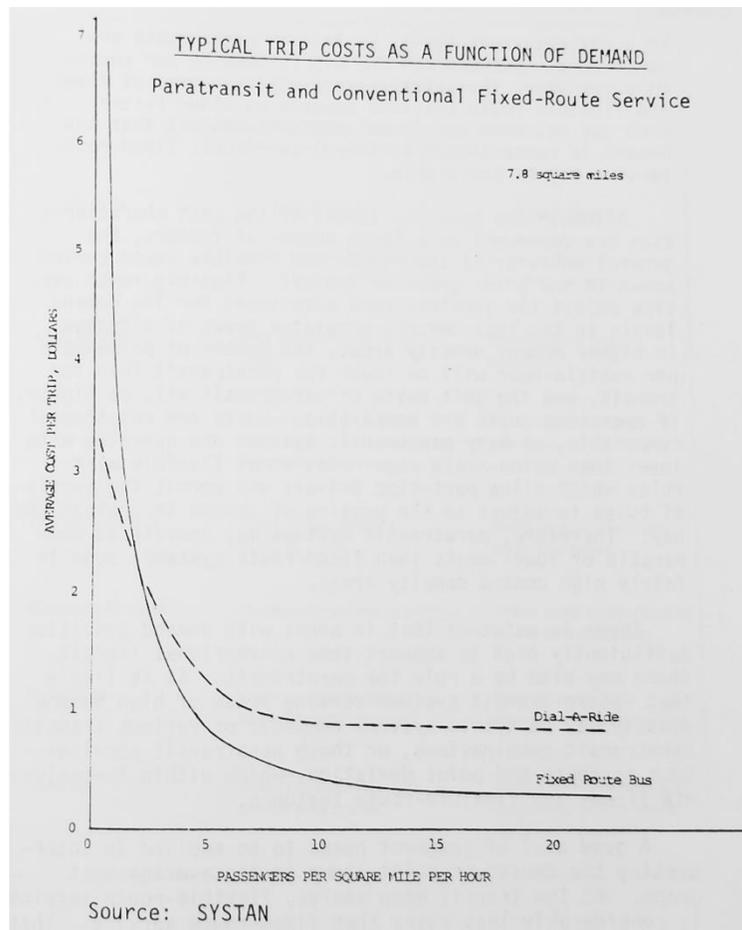


Figure 1.4. Comparison of fixed route transit to DRT (source: Systan, 1980).

More recently, Daganzo and Ouyang (2019) illustrated how the different modal services between fixed route and on-demand may compare under simplified operating settings. **Figure 1.5** shows how the minimum door-to-door passenger travel time (f) versus fleet size (m) for different levels of demand density (π) for a stylized example. It illustrates when fixed route transit (“conventional transit”) is a more preferred option by travelers relative to automobile (“auto”), ride-share, and taxi, and how this region extends out as demand increases.

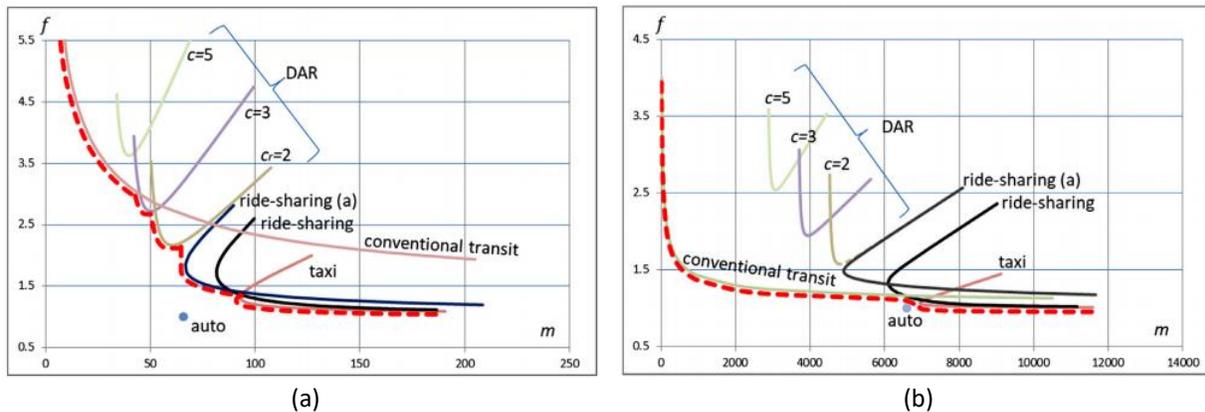


Figure 1.5. Comparison of travel times based on (a) $\pi = 100$ vs (b) $\pi = 10,000$ (source: Daganzo and Ouyang, 2019).

1.2. Compendium Objectives

This compendium serves the role of compiling and synthesizing from this long literature. It includes both classic and emerging methods to design the provision of public transit, focusing primarily on the tactical and strategic decisions as opposed to operational considerations. Based on our synthesis of the literature, the major classes of operations can be broken down into three: fixed route transit, semi-flexible transit, and on-demand microtransit. The goal is to allow a transportation professional working in a public agency or a mobility provider to get a broad overview of the current state of the art and the history that led to this state.

The compendium also covers an in-depth case study that uses a common data set and a simulation evaluation tool constructed by the authors to allow reader hands-on practice to make comparisons between state-of-the-art methods. In a sense, this compendium also serves as an add-on to a book published by Chow (2018) on *Informed Urban Transport Systems: Classic and Emerging Mobility Methods toward Smart Cities*, one that focuses on public transit. In summary, readers should consider this compendium if they are looking:

- To get a broad overview of state-of-the-art public transit tactical and operational methods that consider both fixed and demand-responsive approaches;
- For research problems and challenges that remain unanswered to derive research problem statements;

- To try out state of the art methods in a simulation environment to learn the methods (or teach them to students);
- To take the simulation tool and modify the case study inputs to evaluate other scenarios.

1.3. Compendium Organization

The compendium is organized to provide an overview of three classes of public transit first, followed by a discussion of the challenges facing the industry in terms of hurdles from technology, built environment, market dynamics, and institutional structures. Finally, a section is devoted to an in-depth case study using data from the B63 bus operation in Brooklyn, NYC to illustrate how each class of operation would fare. The three classes include fixed route transit, a semi-flexible transit service in which some stops may vary dynamically with checkpoints, and a fully flexible service that is DRT with door-to-door stops.

- Section 2: fixed route transit
- Section 3: flexible route microtransit
- Section 4: on-demand microtransit
- Section 5: technological and institutional challenges
- Section 6: use case study of state-of-the-art methods
- Section 7: conclusion

Section 2: Fixed Route Transit

Fixed route transit service is the most rigid of the three class of transit covered in this compendium. Certain vehicle technologies require rigid routes, e.g. metro and other railway operations. The general trade-off of using a more rigid operational policy is that much higher passenger flow capacities can be attained and therefore is more suited for high demand density populations. This comparison in capacity for different operating modes is shown in Figure 2.1 from Vuchic (1981), where LRT is light rail, RB is regular bus, RGR is regional rail, RRT is rail rapid transit, SCR is streetcar, and SRB is semirapid bus that includes bus rapid transit (BRT).

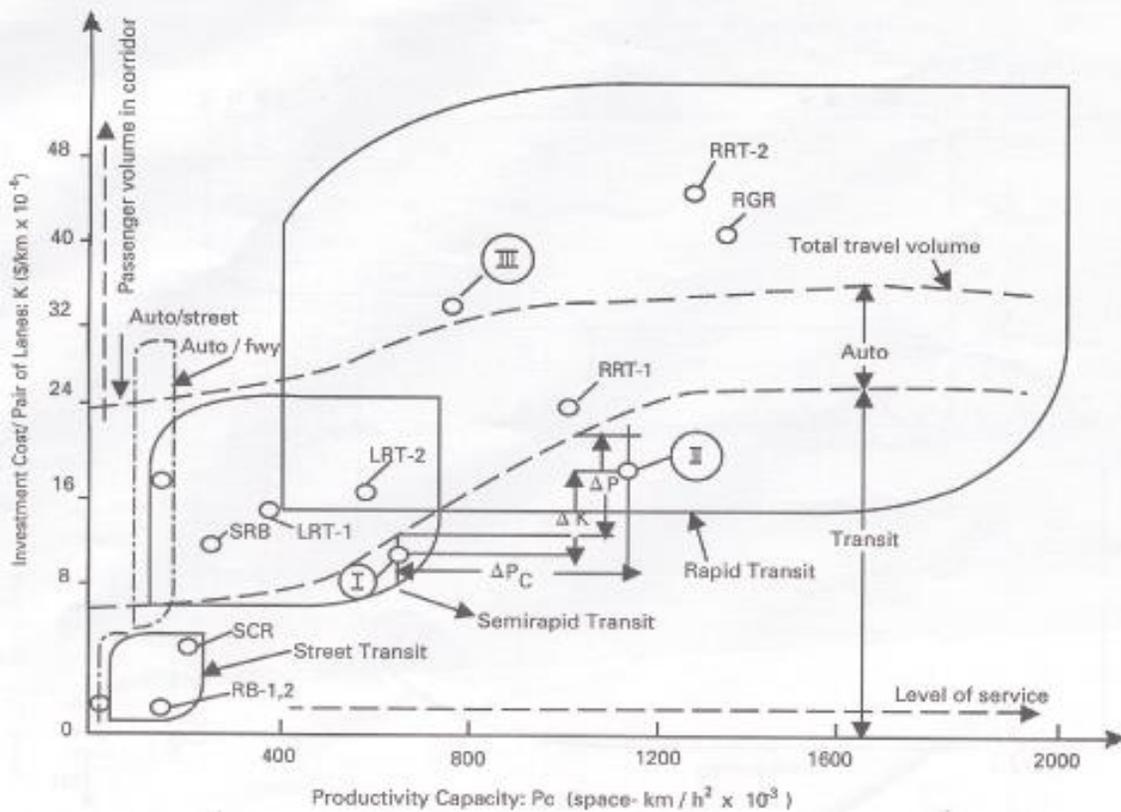


Figure 2.1. Relationship between productive capacity, investment cost, and passenger attraction of different fixed route transit services (source: Vuchic, 1981).

Fixed route transit service operational planning involves several key functions outlined by Ceder (2016) in **Figure 2.2**: network route design, timetable development, vehicle scheduling,

and crew scheduling. Network design determines the structure and service of the network, including determination of routes and stops. Timetabling cements these route-level decisions with frequencies or headways along with a public timetable. Vehicle scheduling assigns the fleet to the timetables while crew scheduling assigns drivers and other staff to the fleet operations. The appropriate vehicle technology and size can be chosen to match the requirements of the system heretofore designed. Timetabling, vehicle scheduling, and crew scheduling constitute tactical planning. Beyond that, operational control decisions also need to be made. As such, this section is divided into those three categories: strategic planning, tactical planning, and operations.

2.1. Strategic planning

Strategic planning involves planning routes and frequencies, often called the line planning problem. Hasselström (1982) and van Nes et al. (1988) proposed early line planning optimization models for setting routes and frequencies jointly. **Figure 2.3** illustrates how two different transit route networks can be designed over a test network given different demand conditions. Focusing on rail rapid transit, López-Ramos et al. (2017) combined network design and frequency setting into a single mathematical formulation.

More recent work on line planning and network design has introduced new optimization objectives reflecting specialized use cases. For example, Pternea et al. (2015) presented a model for solving the network design problem oriented towards sustainability by incorporating electric vehicles and adding a vehicle emissions term into the objective function. Liu and Zhou (2016) solved the dynamic version of the transit network design problem, which incorporates time varying schedules and stops. Cats and Glück (2019) jointly solved for optimal frequencies and vehicle capacities using a dynamic transit assignment model. Their results highlight opportunities for mixed fleet sizes and asymmetric service provision. Real-time mass transport network optimization problems and their solutions were explored by Pagés et al. (2006), who proposed a global solution algorithm to solve a mass transport network design problems (MTNDP). The optimization process was solved by means of a three-level hierarchical approach:

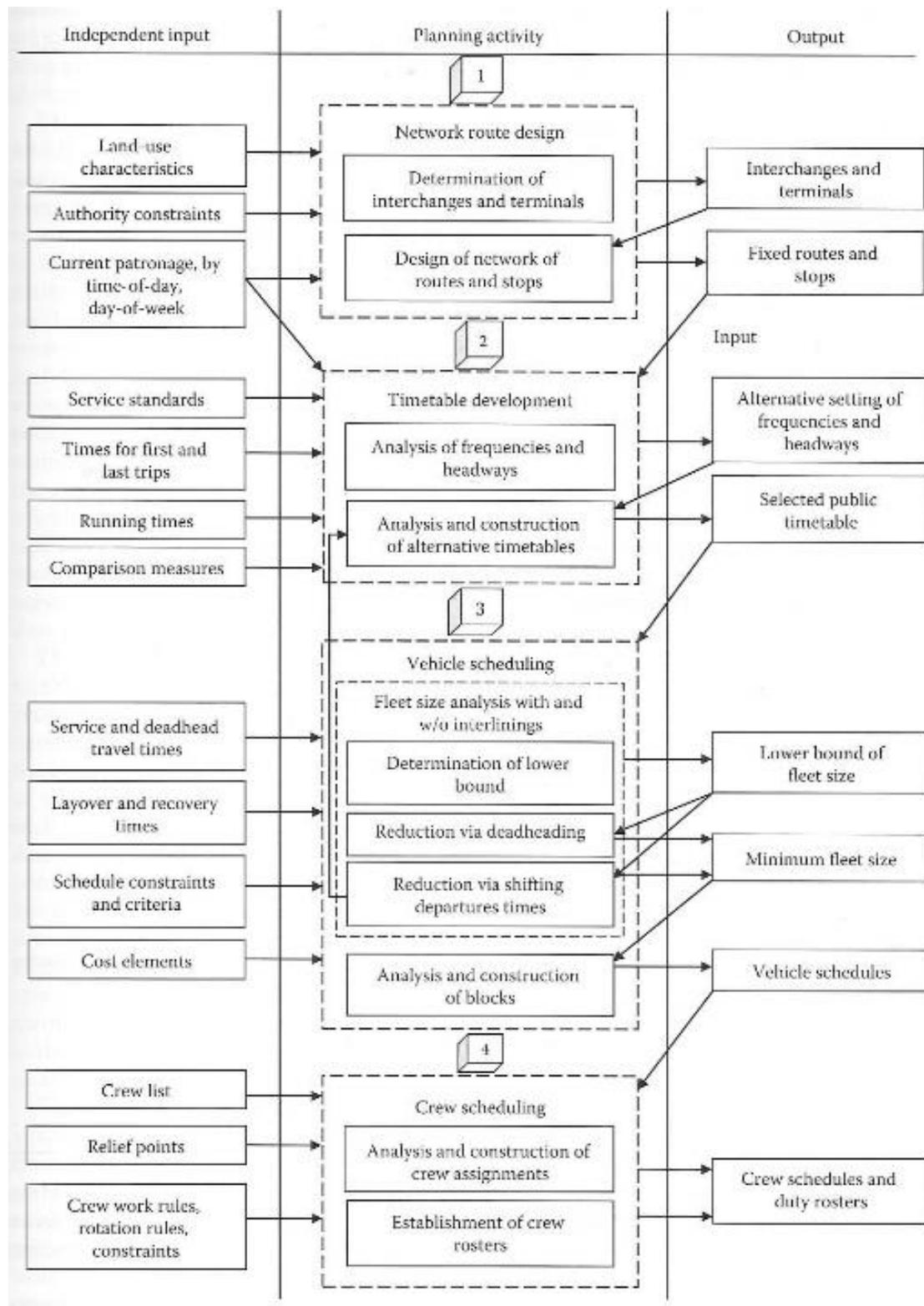


Figure 2.2. Functions associated with fixed route transit operations planning process (source: Ceder, 2016).

a framework for estimating the pure transfer penalty in minutes using a combination of stated and revealed preference surveys. They performed a case study in Madrid, Spain, and found that the pure transfer penalty is similar to a 15-18 minutes increase of in-vehicle time. Schakenbos et al. (2016) used mixed logit models to evaluate the multimodal transfer penalty between feeder transit modes and passenger rail in the Netherlands. They found transfer penalties averaging 40 minutes of generalized travel time.

Reviews of transit network design models and algorithms can be found in Guihaire and Hao (2008) and more broadly in Farahani et al. (2013). Line planning has been shown to be NP-Hard in complexity (see Schöbel and Scholl, 2006) leading to the use of route construction heuristics like Ceder and Wilson (1986). As such, line planning in practice may involve using permutations of simple structures. Fielbaum et al. (2017) explicitly tackle the problem of defining any city transit network using a parameterized network design structure. With many modern cities exhibiting more density complexity than a single, central business district (CBD), they propose a model for cities based upon a CBD and n zones, each zone having a sub-center and periphery. Peripheries generate trips, the CBD attracts trips, and subcenters do both. Fielbaum et al. (2016) used their network description to evaluate four different line structures: direct lines, exclusive lines, hub-and-spoke, and feeder-trunk. These are shown in **Figure 2.4**.

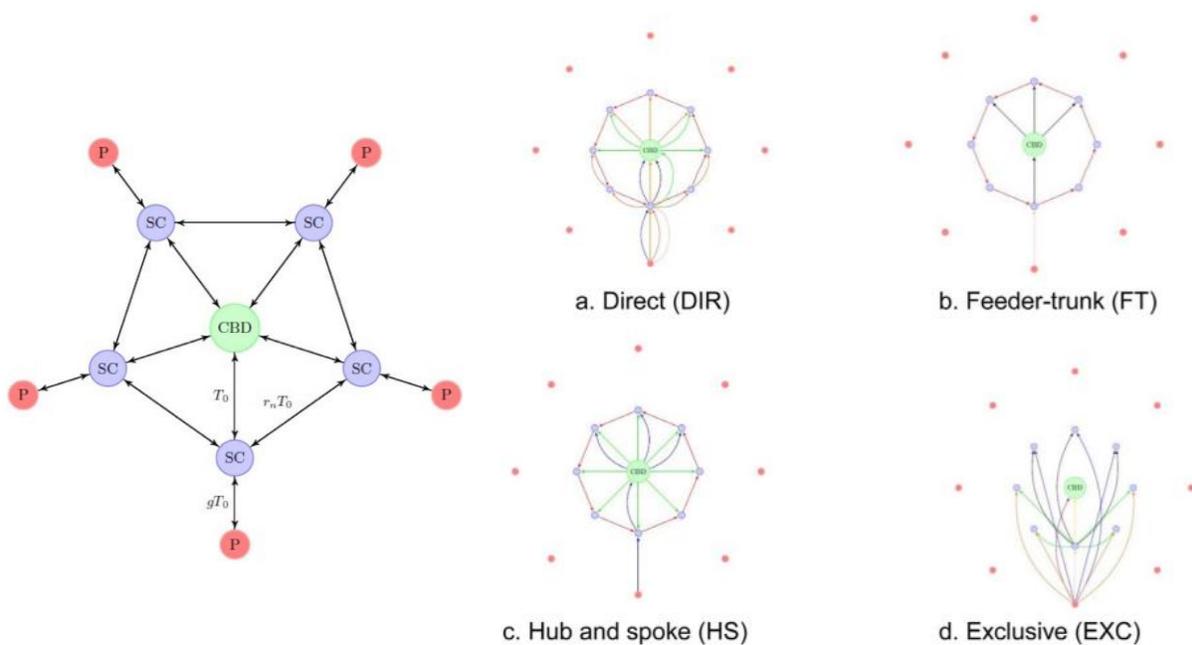


Figure 2.4. General network design that can be parameterized into different structures: (a) direct, (b) feeder-trunk, (c) hub and spoke, and (d) exclusive (source: Fielbaum et al., 2016).

- **Direct lines structure.** Due to inability to collect trips, direct lines do not work well for dispersed cities but are optimal when most of the trips are radial. It presents the largest in-vehicle times (because it uses routes that are not necessarily the shortest ones).
- **Exclusive lines structure.** It requires many small buses, exhibiting large waiting times which increases both operators' and users' costs. It presents the smallest in-vehicle times because there are no intermediate stops. It is competitive only when patronage is large.
- **Hub and spoke.** It would be the best structure for the users if transfers were not penalized. Collecting trips allows high frequencies and low in-vehicle times. The fleets are not big, but the vehicles need a large capacity, so it is not always optimal for the operators.
- **Feeder-trunk.** It is a good structure if and only if the city is dispersed because in that case its low idle capacity allows an efficient combination, yielding a balance between fleet sizes and vehicle capacities.

For those interested in optimizing more custom designs, Byrne (1975) developed a continuous approximation model to optimize transportation line locations and headways for a region with uniform population density and demand. Newell (1979) also developed a model of this type to compare two bus network designs over a square street grid as shown in **Figure 2.5**.

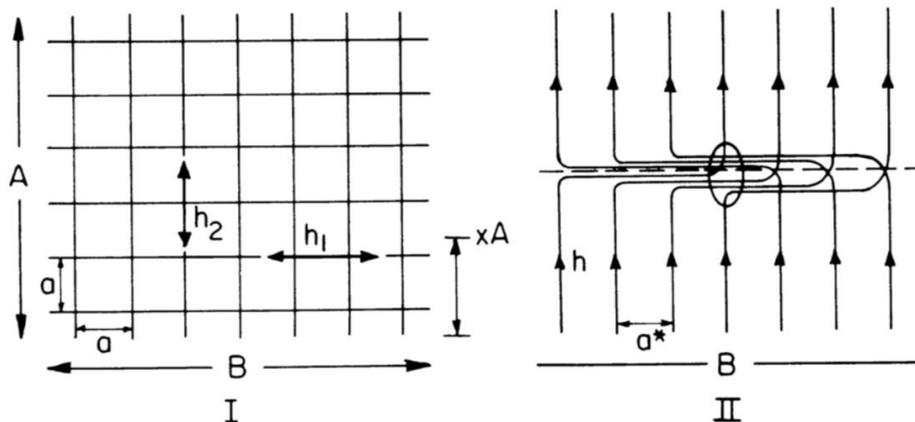


Figure 2.5. Two routing schemes for a rectangular region: (I) perpendicular linear routes vs (II) parallel L-shaped routes (source: Newell, 1979).

Newell assumes uniformly distributed origins and destinations, and that no traveler will make more than one connection to serve their trip. The following parameters in **Table 2.1** are used.

Table 2.1. Parameters for designing grid and hub-spoke networks

a	Distance between neighboring routes in geometry I
a^*	Distance between neighboring routes in geometry II
A	North-South span of the region
B	East-West span of the region
γ_a	User cost of access distance per mile
γ_o	Operator cost per unit time
γ_r	User cost of riding per passenger mile
γ_w	User cost of waiting per unit time
h_1	East-West headway in geometry I
h_2	North-South headway in geometry I
h	Headway in geometry geometry II
ρ	Spatial density of trips made per unit time

Assuming no passenger transfers more than once, each passenger must wait for both an E-W and N-S bus in geometry I. Assuming an average wait time equal to one half of the headway, the average waiting cost to the passenger is $\frac{1}{2}(h_1 + h_2)\gamma_w$. Holroyd (1965) showed that the total average access cost at both ends of the trip is $\frac{1}{2}\left(\frac{23}{30}\right)a\gamma_a$. For a system with two-way service on each route, the total operating cost per unit time is $2\frac{AB}{a}\left(\frac{1}{h_1} + \frac{1}{h_2}\right)$. The average operating cost per trip is then $\frac{2}{a}\left(\frac{1}{h_1} + \frac{1}{h_2}\right)\frac{\gamma_o}{\rho}$. If origins and destinations are uniformly distributed across the region, then the average distance of travel is $(A + B)/3$ leading to an

average riding cost per passenger of $\gamma_r(A + B)/3$. Combining each of these cost contributions leads to Eq. (2.1).

$$C_I = \frac{1}{2}(h_1 + h_2)\gamma_w + \frac{1}{2}\left(\frac{23}{30}\right)a\gamma_a + \frac{2}{a}\left(\frac{1}{h_1} + \frac{1}{h_2}\right)\frac{\gamma_o}{\rho} + \frac{A + B}{3}\gamma_r + \gamma_t \quad (2.1)$$

For the parallel network of geometry II, the average waiting cost in this case is simply the headway times the cost per unit time: $h\gamma_w$. The maximum access distance is $\frac{a^*}{2}$, assuming uniform demand density, the average access distance $\frac{a^*}{4}$. Thus, the total average access cost considering both trip ends is $\left(\frac{a^*}{2}\right)\gamma_a$. The operating cost per unit time is $\left(A + \frac{B}{2}\right)\frac{B}{a^*}\left(\frac{1}{h}\right)\gamma_o$. The average cost of operation per trip (assuming service in both directions) is $\frac{2}{a^*h}\left(1 + \frac{B}{2A}\right)\frac{\gamma_o}{\rho}$.

Nearly all trips served using geometry II need to travel to the central line, unless a user's origin and destination just happen to be located on the same line. Therefore, the average N-S riding distance is $A/2$ while the average E-W riding distance is still $B/3$, so the total average riding cost per passenger is $(A/2 + B/3)\gamma_r$. The cost expression is shown in Eq. (2.2).

$$C_{II} = h\gamma_w + \frac{a^*}{2}\gamma_a + \frac{2}{a^*h}\left(1 + \frac{B}{2A}\right)\frac{\gamma_o}{\rho} + \left(\frac{A}{2} + \frac{B}{3}\right)\gamma_r + \gamma_t \quad (2.2)$$

One can optimize these equations for the optimal headways and line spacings to find which network design is best suited for a given scenario.

If the routes are given, frequency setting is a key determinant of how much service to allocate along a route. Newell (1971) developed a model to set the service rate on a single route with a time-varying level of demand by minimizing the sum of user cost of delay and operator cost. His finding that the optimal frequency is proportional to the square root of the arrival rate of passenger is sometimes referred to as the square root rule. Mohring (1972) independently showed a similar square root rule using a simpler construct of the cost function. The objective in that study was to show that with user cost considered, transit frequency for a given route exhibits economies of density, which serves as evidence for public subsidies of transit service.

Mohring considers a mile of a steady-state, directionally balanced bus route with the following parameters in **Table 2.2**.

Table 2.2. Parameters for Mohring’s route cost function

B	Number of boardings (and exits) per hour of all buses. Origins and destinations are uniformly distributed along the route.
M	Length of each passenger’s trip.
x	Number of buses that traverse the route segment each hour
C	Cost of providing bus service in dollars per hour
Y	Number of uniformly spaced bus stops per mile
γ	Speed at which passengers walk to and from bus stops
β	Fraction of one headway that the average passenger waits for a bus
V	Average value of in-vehicle time in dollars per hour
α	Ratio of the value of walking and waiting time to in vehicle time
S	Overall average speed of a bus in miles per hour
S^*	Cruising speed of a bus
ϵ	Time required for one passenger to board or alight, in hours
δ	Time added to the time required to traverse the route by each starting and stopping maneuver

Mohring divides the total hourly costs into four components: operator costs; and passenger costs of access, waiting, and, in-vehicle time. For operator costs, the bus will spend $\frac{M}{S}$ hours, on average, to travel the route, and x buses per hour circulate at a cost of C dollars per hour per bus. This gives a total operator cost of $\frac{CxM}{S}$ dollars per hour, and a cost per passenger served of $\frac{Cx}{BS}$. The distance between neighboring stops is $\frac{1}{Y}$ miles, so the maximum distance a bus

customer will need to walk is half of this, $\frac{1}{2Y}$. Assuming uniformly distributed demand, the average passenger will walk $\frac{1}{4Y}$ to their pickup bus stop and $\frac{1}{4Y}$ from their dropoff bus stop for a total walk distance per passenger per trip of $\frac{1}{2Y}$. The cost of this walking distance is $\frac{\alpha V}{2\gamma Y}$ dollars. The average rider will wait at the bus stop for $\frac{\beta}{x}$ hours and the cost of this average wait is $\frac{\alpha V \beta}{x}$ dollars. The cost of in-vehicle time is $\frac{MV}{S}$. Summing each of these terms yields a total cost per passenger of the route in Eq. (2.3).

$$Z = Cx/BS + \alpha V/2\gamma Y + \alpha V\beta/x + MV/S \quad (2.3)$$

Mohring's analysis assumes that overall bus speed S is independent of the rate at which vehicles are provided, x . If demand is fixed, one would expect that lower bus frequency would result in lower overall speed because the queue of passengers at each bus stop might be longer, and dwell time in boarding movements will occupy a larger share of each bus's tour. Putting that consideration aside for the time being, differentiating Eq. (2.3) with respect to x and setting equal to zero determines the minimum-cost value of x shown in Eq. (2.4).

$$x^* = \sqrt{\frac{\alpha V \beta B S}{C}} \quad (2.4)$$

The model suggests that under an objective of minimizing *both* user and operator costs in setting service frequency, there are always economies of scale present. As a result, it is beneficial to consider public subsidies to increase service frequency.

Newell's analysis treats the demand as a time-varying function, but if we instead take demand to be constant (as Mohring does) and apply Mohring's notation from above, Newell's solution for the cost-minimizing headway is $x^{-1} = \sqrt{\frac{a}{\beta B}}$ where a is a measure of the per vehicle

operator costs². In Mohring's terms, $a = C/S$, and if we substitute that into the above, we see that this is nearly equal to Mohring's relationship in Eq. (2.4). The only difference results from Mohring's weighting of waiting time by a factor of αV , whereas Newell is primarily concerned with the operator perspective, and thus treats all costs as nominally equivalent.

Analytical models of this square-root form are still of use to contemporary researchers, even beyond the policy implications for subsidy (Parry and Small, 2009). Tirachini et al. (2010) derived a relationship of this type for use within a technology choice model. Laporte and Moccia (2016) elaborated on Tirachini's work in their technology choice model, adding variable stop spacing, variable train length, a crowding penalty, and a multi-period generalization to the base model.

An alternative approach to analytical models is using mathematical programs that optimize the frequencies subject to constraints. In one of the most cited studies across the literature, Furth and Wilson (1981) present a non-linear program that treat frequency setting as a resource allocation problem. Gkiotsalitis and Cats (2018) set up their problem formulation to explicitly optimize for the reliability of the headways in question, i.e. mitigating against inherent variability across the network.

Stop-spacing is the oldest documented problem in public transit network design, dating back to several German papers in the early 20th century. Vuchic and Newell (1968) were some of the earliest to revive the question in the American context when they presented a model for inter-stop spacings for minimum travel time, although their model is equally applicable to any fixed-route mode. Wirasinghe and Ghoneim (1981) derived a continuum approximation model for the optimal stop spacing given a curvilinear street grid. Their results give the optimal spacing as a slowly varying function along the position of the route that relates to the square root of the ratio of bus passengers passing a point to the daily demand for boarding and alighting at that point. They also adjust their model to account for the possibility that an individual bus need not service bus stops for which there are no requested pick-ups or drop-offs.

² Newell assumes the value of Beta to be 0.5, as is typical across the literature.

Optimal spacing can be derived for a single line similarly to optimal frequency, by setting the total cost function and taking the derivative of the function with respect to stop spacing. When trying to solve jointly for both stop spacing and frequency, there is no analytical expression for the optimum. However, if frequency is held fixed, then taking the derivative of the cost function with respect to stop spacing and setting it equal to 0 produces a similar square root expression shown in Eq. (2.5), where S is number of stops, P_a is the value of access time, L is the route length, N is the passenger demand, v_w is walking speed, t_s is stopping delay in addition to time spent by transfer of passengers, c is an operating cost per bus per hour, f is bus frequency, P_v is value of in-vehicle time savings, and l is the average passenger travel distance (see Tirachini, 2014).

$$S^* = \sqrt{\frac{P_a L N}{2v_w t_s (c f + P_v \frac{l}{L} N)}} \quad (2.5)$$

This equation shows that optimal number of stops (S^*) increases with increasing value of access time savings, route length, and demand, and decreases with increasing frequency, value of in-vehicle time savings, and trip distance. Tirachini also notes that this equation does not capture the interaction between changes in demand and level of service improvements, but that is consistent with best practices for Bus Rapid Transit systems, which generally serve higher demand at longer stop spacings and higher cruising speeds.

A limitation of these continuum approximation models is that they generally rely on assumptions of uniform demand. Furth and Rahbee (2000) instead take a discrete approach in which each intersection along a bus line is a candidate for a stop, and exogenous non-uniform demand is allocated depending on the selections. An application of their work on a bus route in Boston supports doubling the average stop spacing over the length of the route, saving \$132 per hour in social costs. More recent work has focused on heterogeneous demand patterns and specialized services. Chen et al. (2016) cluster stops based on land use patterns and apply different optimal stop spacings based on land use type, resulting in a 3% social cost savings over the tram route of interest. Zhu et al (2017) optimize mini-bus stop spacing for a feeder route to a rail station.

Certain public transport markets feature a small number of competing actors rather than a single, centralized entity. Li et al. (2012) develop an integer programming model of this case to

optimize the number of operators and the allocation of lines. They find that the introduction of new lines has a sizeable effect on equilibrium fares and frequencies on existing lines, and that, due to economies of scale, the allocation process favors larger enterprises. Chow and Sayarshad (2014) classify interactions between coexisting systems using symbiotic relationships: in mutualistic relationships the improvement of one system benefits another while in parasitic relationships the improvement of one system occurs at the detriment of the other, conceptually illustrated in **Figure 2.6**. Understanding the right type of relationship between different mobility operators is important for enabling MaaS.

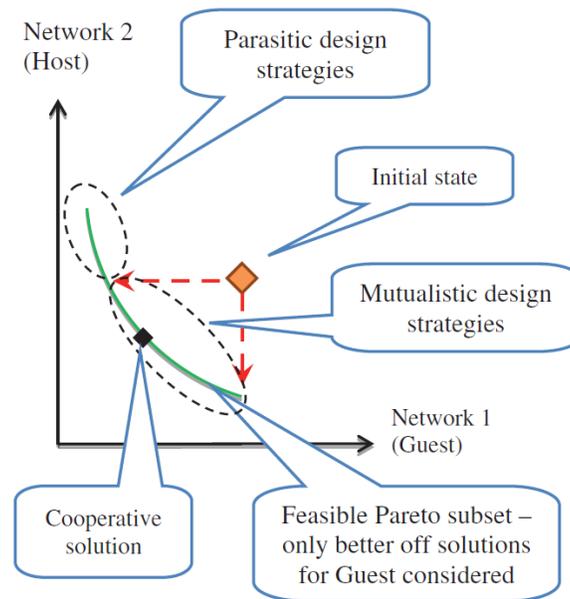


Figure 2.6. Illustration of decision space as a result of design strategies from “guest” operator (source: Chow and Sayarshad, 2014).

2.2. Tactical Planning

Once the network structure is set, the service pattern of each line must be decided. For traditional fixed-route service, this consists of developing timetables for service and crew scheduling.

Timetabling is the task of enumerating all the times at which a vehicle will service each stop. This process is the transition point between public transportation planning and operations. The timetable is the output of all planning steps, and the first input to vehicle and

crew scheduling. In a basic sense, timetabling is relatively simple. Assuming constant headways and demand, one can propagate the policy headway across the hours of operation for each route (Desaulniers and Hickman, 2007). Headways should not necessarily be constant in many cases, and Ceder (1987) provides a practical guide to timetabling with equal, balanced, or smooth headways based on current ridership counts.

The timetabling process becomes more complex once the objective of synchronization across routes is introduced. Bookbinder & Désilets (1992) minimize the inconvenience of bus transfers by choosing the offset times between feeder and trunk routes while also considering the stochastic nature of travel time through simulation. Their integer programming model is not suited for solving networks of the scale of most real-world systems, so Ceder et al. (2001) present a heuristic that solves for a set of timetables with maximal synchronization for larger problem sizes.

Emerging methods for timetabling rely on new data sources and technologies. Yap et al. (2019) present a new passenger-oriented and data driven methodology for setting timetables for large scale networks based on automatic fare collection data. Their method reduces the size of the problem by predetermining the most important transfer hubs and the most important lines using each of these hubs. Looking towards the future, Cao and Ceder (2019) devise a method for timetabling and vehicle scheduling of an autonomous shuttle bus service. Such a service could easily operate cognizant of exact origin and destination demand for its users, so their method incorporates a real time skip-stop strategy to increase efficiency.

Most fixed route transit services are designed to have equal capacity in both directions along a line. This conflicts with prevailing demand patterns, which tend to be directionally imbalanced - especially at the peak demand periods. One operational adjustment to address this is alternate deadheading, in which a fraction of vehicles that would serve the low-demand direction instead return directly to the opposite terminus without serving any customers (known as “deadheading”) to then begin another run in the peak demand direction. Furth (1985) developed a model for alternate deadheading that, when applied to a representative bus route, showed potential for significant fleet size reduction.

Some transit lines feature consistently high levels of demand only within a certain corridor. In this scenario, short turning bus routes may better allocate resources by dedicating a portion of vehicles to only serve the high demand section. Conceptually, it’s identical to alternate deadheading, but short-turning serves both sides of the street on this limited route. Short turn

policies lead to unequal vehicle loads if headways are evenly split between the full-length and short-turn services. Furth (1987) explains how in this case, short-distance riders board either bus to arrive first while long-haul riders only board the full-length bus. Therefore, demand is unevenly weighted towards the full-distance service, and unused capacity on short-turn buses are not matched to short-distance riders on crowded full-distance buses.

The solution to this problem is a careful schedule coordination that runs the short turn pattern fractionally ahead of the full-length vehicles, allowing them to siphon off more of the short-distance demand. Furth provides a full guide to designing short-turning patterns, including schedule coordination, the locations of turnback points, vehicle sizes, headways, and offsets. Application to a real bus route in Los Angeles indicated that short turning patterns designed in this way could reduce required fleet size from 35 vehicles to 24.

Short-turning is equally applicable to rail systems, and Canca et al. (2016) apply the strategy as a means to compensate for service disruptions due to high demand along a rail line. They present a mixed integer linear optimization model to find optimal service patterns and include a simulation tool to estimate vehicle occupancy.

The complement to short turning is express or limited stop service, wherein the service area receiving a high level of service is not in the middle of the route, but instead at either end. Jordan and Turnquist (1979) refer to this service pattern as “zone scheduling,” and present a dynamic programming model that searches for zone scheduling policies to maximize reliability and minimize travel time. Their results show zone scheduling reduces both average trip times and fleet size while improving reliability. Furth (1986) extend this model to bi-directional routes for local alighting in the inbound direction and local pickups in the outbound direction, with similarly encouraging results. Torabi and Salari (2019) search for limited stop schedules to reduce the fleet’s unused capacity and find improvements of 35% to 48% depending on demand concentration. Chen et al. (2015) incorporate capacity constraints and stochastic travel times in their search method for correlated limited-stop schedules in which each stop along a route is never skipped by two vehicles in a row.

2.3. Operational control

To this point, the planning process has been moving towards developing a network of fixed route transit lines each with a predetermined and regular structure and service pattern.

Investigating service patterns around the periphery of that assumption can yield benefits for real-world systems. As categorized here, alternative service patterns do not require real time information such as automatic vehicle location. However, they may be dynamic in the sense that their outputs may result in time-varying behavior.

One such real-world complication is bus bunching. On high frequency routes, irregularity in travel time can result in buses arriving in bunches or platoons. This phenomenon increases both average wait time and wait time variability (Bartholdi and Eisenstein, 2012). Among the simplest responses to combat bus-bunching are holding strategies that delay an otherwise unobstructed vehicle in order to “smooth” the service pattern. Osuna and Newell (1972) develop a model for the optimal holding strategy at a single control point by minimizing the overall passenger wait time. Daganzo (1997) established a framework for extending this to a multiple control point strategy in systems for which stop skipping is not a feature. In modern practice, bus bunching and headway control are best addressed by taking advantage of real time information. Methods of this type are addressed in the Real Time Control section.

With the widespread adoption of real time location information and other information systems across transit, many of the alternate service patterns addressed above can be pursued in a more intelligent manner. Bus bunching especially benefits from real time control strategies because high frequency bus arrivals are inherently unstable, so active control is required to smooth them (Newell and Potts, 1964).

Daganzo (2009) presents a method for holding based on real time headway information that quickly responds to disruptions based on a limited data feed. One limitation of Daganzo’s proposed approach is that it cannot compensate for the most severe disruptions because the leading vehicle will proceed unimpeded, leaving a large gap in its wake that will then continue to slow down the following buses. Solutions to this difficulty generally predict the next arrival based on available real time information. Daganzo and Pilachowski (2011) present a model of this type that equalizes the forward and backward headways by modulating the bus cruising speed and holding time. Bartholdi and Eisenstein (2012) develop a simple headway-based holding scheme that self-equalizes based upon the predicted time between the bus of interest at the control point and the trailing bus. Their method is robust to arbitrary changes in service capacity (i.e. adding vehicles), making it even simpler to modify than naïve schedule-based approaches.

Rather than predict the vehicle arrivals as a closed form estimate, Berrebi et al. (2015) base predictions on a probability distribution of future arrivals. In a subsequent publication, Berrebi et al. (2018) compare all the above real time holding methods and apply them to a real bus route in Portland, Oregon. Their case study shows the method of Daganzo and Pilachowski to be the most effective for short holding times, and that of Berrebi et al. (2015) better suited to situations in which longer holding times are possible. Wu et al. (2017) optimize real time holding policies using a bus propagation model that incorporates bus overtaking and more realistic passenger boarding. Compared to holding strategies that ignore these two factors, their results show improvement in both simulation and in a real bus route. These adaptations are best suited for modelling high frequency bus lines where vehicles often proceed in tight platoons, overtaking back and forth, and serving some stations contemporaneously.

Real time control can also be leveraged to optimize operations for maximum transfer coordination. Nesheli et al. (2016) simulate bus line operations using a “library of tactics” to improve transfer connectivity and use holding strategies to reduce missed transfer waiting time by 91.5%.

Furth and Muller (2000) test a system of conditional bus priority experimentally on a bus line in Eindhoven, Netherlands. The system is meant to reduce impacts to disruptions. Their results show the conditional priority policy improves schedule adherence relative to no priority, while avoiding negative traffic impacts of an unconditional priority policy. These results are shown in **Figure 2.7**. Anderson and Daganzo (2019) formalize conditional signal priority in a mathematical model for simulation. Their simulation results show similar relative performance relative to Furth and Muller (2000). Even simplistic, limited signal-based interventions have yielded positive results. Estrada et al. (2016) combine vehicle speed control with dynamic green time extension and find improvements in total system cost and headway reliability.

Many other transit operation patterns can be reformulated to reflect the availability of real time information and control. Eberlein et al. (1998) revisit the Alternate Deadheading problem studied by Furth and adapt it to a real-time decision process. As they define it, “The real-time deadheading problem (RTDP) then is to decide, at any given time at a terminal, which vehicles should be deadheaded and how many stations should be skipped by each deadhead vehicle in such a way as to minimize the total passenger cost.” By formulating the RTDP as a nonlinear integer programming problem and applying it to a bus route in Boston, they show passenger wait time improvements of 12% – 20%.

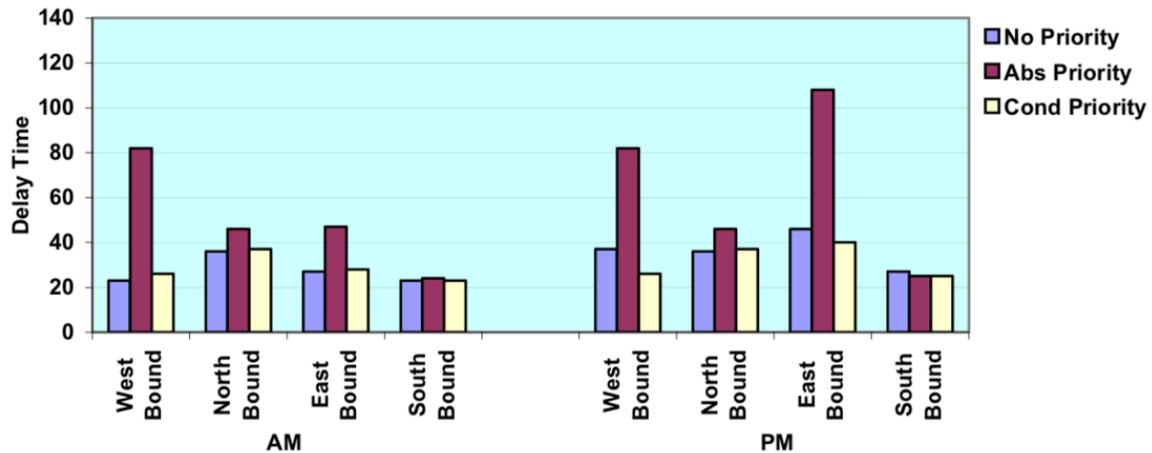


Figure 2.7. Average Vehicular Total Delay (seconds) under different signal priority policies (Furth and Muller, 2000).

Another strategy to re-allocate vehicles between routes is to station standby vehicles in intermediate locations to be called into service if needed to fill large gaps. Petit et al. (2018) devise optimal policies for bus substitution on a single line under multiple scenarios that reduce system and passenger costs. They also note promising opportunities for future work in extending this model to sharing buses across multiple routes and designing for the substitution of autonomous vehicles. Sayarshad and Chow (2017) use queueing to approximate future costs to relocate idle vehicles.

Real time stop-skipping decisions can improve transfer synchronization and bus bunching. Sun and Hickman (2005) are the first to formulate this real time stop-skipping problem, allowing onboard passengers to be dropped at their planned destinations while still “expressing” past others. They showed it can be solved in real time through an explicit enumeration method, making it readily implementable if the data is available.

Guo et al. (2018) propose a model to optimally time when to switch between two alternating service modes where there are asymmetric switching costs. The authors consider the switching costs that create two thresholds for switching (Q_L : threshold from a high demand mode to a lower demand mode, and Q_H : threshold from a lower demand mode to a higher demand mode). When the switching costs approach zero, the thresholds should converge to a single value. The proposed policy in this study is based on market entry-exit switching option i.e., to simulate the dynamic evolution of the demand density ($Q(t)$), and

- switch to FRT whenever $Q(t) > Q_H$ or

- switch to flexible transit whenever $Q(t) < Q_L$.

An illustration of a monitored system that switches between fixed route service (high demand) and flexible on-demand service (low demand) is shown in **Figure 2.8**. The figure shows how the system starts out operating as a flexible transit and waits until the demand crosses Q_H at t_1 before it would switch to fixed route transit. Afterwards, the system would stay in fixed route service until demand drops below Q_L at t_2 before switching to flexible transit. The threshold values Q_H and Q_L are derived from real options theory for market entry-exit conditions. Example applications include switching vehicle sizes, peak and off-peak operations, and route configurations.

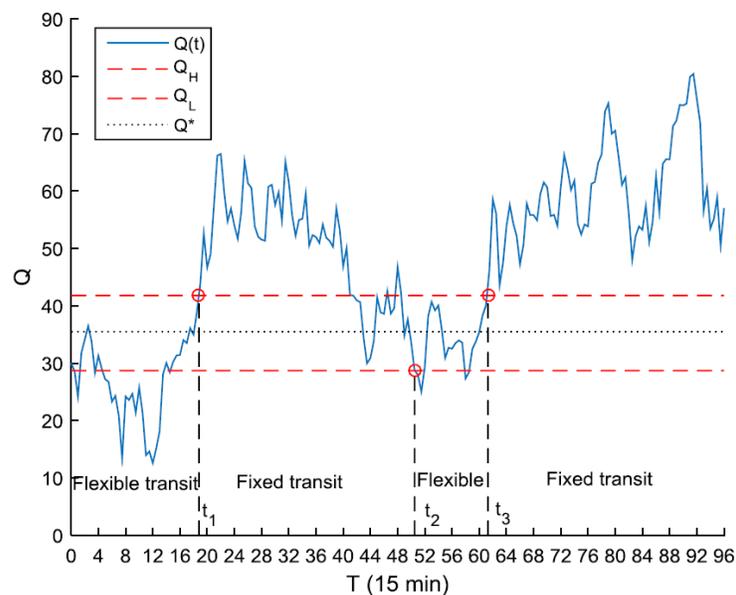


Figure 2.8. Illustration of switching policy between fixed and flexible transit using real options theory (source: Guo et al., 2018).

It was noticed that a hysteresis effect exists where there is a cost of switching, and this effect is sensitive to transportation system conditions and demand characteristics. When switching cost increases, it is better to wait long before intervening. This study may be applied to determine when to allow fixed-route services to deviate, optimal holding strategies for buses, adjusting a fleet of vehicles to be dispatched, positioning of idle on-demand vehicles, or determining price surges.

Table 2.3 summarizes some of the areas where real time control has been applied.

Table 2.3. Examples of real time control strategies

Type of strategy	Reference(s)
Vehicle holding to control for bunching	Daganzo (2009), Daganzo and Pilachowski (2011), Bartholdi and Eisenstein (2012), Berrebi et al. (2015)
Vehicle holding to reduce missed transfer waiting time	Nesheli et al. (2016)
Conditional bus priority	Furth and Muller (2000), Anderson and Daganzo (2019)
Vehicle speed control and signal priority	Estrada et al. (2016)
Alternate deadheading	Eberlein et al. (1998)
Vehicle repositioning	Petit et al. (2018), Sayarshad and Chow (2017)
Stop-skipping	Sun and Hickman (2005)
General mode switching	Guo et al. (2018)

2.4. Transit Technology Selection

In an ideal sense, transit technology selection should be the capstone decision in the transit system planning process - taking the outputs of network design and service characteristics and matching those requirements to an appropriate design alternative. While this segmentation is rarely possible in practice, technology selection models are valuable either as a validation measure or to compare two similar alternatives.

The transport technology decision is multi-dimensional and interwoven. Components of vehicular technologies include the support, guidance, propulsion, and control, and in some cases these components are mutually dependent and coupled (e.g. for light rail vehicles, the support and guidance are both performed by steel tracks) (Vuchic, 1981). Furthermore, this choice impacts operators, passengers, elected officials, and the surrounding community - each of whom often hold competing objectives. The literature offers tools to help resolve this complex decision for a given scenario.

Parajuli and Wirashinghe (2001) develop a multi-objective utility model for public transportation technology selection that combines the utility to operator, users, and community into a single function. This function uses the right of way category, operating rules, level of demand, and unit cost parameters as its inputs. The authors incorporate this function into a multi-event model whereby the parameters undergo random variation to model the unpredictable realities of forecasting.

The underlying demand pattern, both temporally and spatially, is an important determinant of technology selection. Kim and Schonfeld (2013) show that a mixed fleet variable type bus operation can decrease provider costs under these varying circumstances by scaling between fixed-route service with large vehicles and demand-response service with small vehicles. Some authors limit themselves to specific demand patterns in order to address specialized transport users. Sun et al. (2017) take a geography-neutral commuter corridor and determine the optimal length of a rail line for a given demand level served by feeder-trunk bus service.

Daganzo (2010) develops an analytical model for network structure and technology choice (bus, bus rapid transit, or metro) along a corridor assuming uniform demand. His analysis shows hub-and-spoke networks are most efficient for expensive infrastructure costs, bus rapid transit competes with automobile in most cases, and if the city has enough available right of way, bus and bus rapid transit outperform metro systems. Illustrations of the stylistic network structures are shown in **Figure 2.9**.

Tirachini et al. (2010) also present an analytical model for the choice between bus and rail. They find buses to be more cost effective overall, but as demand increases, so does the probability that comparatively faster rail service will be the more cost-effective alternative. They also show that a rail system is better suited to maximizing social welfare than to maximizing profits.

Moccia and Laporte (2016) extend the model of Tirachini et al. to include optimal stop spacing, optimal train length, a crowding penalty, and generalization over multiple demand periods. They too find that the road-based modes dominate, and, using system parameters from the literature, calculate the breakeven demand between bus rapid transit and light rail to be around 13,000 pax/hr and the point between light rail and heavy rail at 20,000 pax/hr. Moccia et al. (2017) further extend this work to incorporate an elastic demand model and show that the basic conclusions remain unchanged. A separate study refines the model to include

more detail related to specific operating scenarios of bus rapid transit and light rail transit (Moccia et al., 2018).

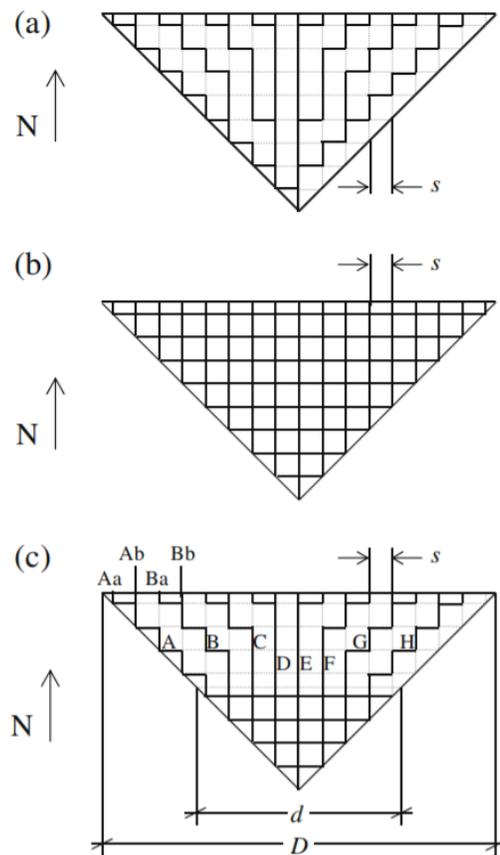


Figure 2.9. Comparison of different transit structures: (a) hub and spoke, (b) grid, and (c) hybrid (source: Daganzo, 2010).

Mendes et al. (2017) conduct one of the first comparisons between light rail and a fleet of shared autonomous vehicles operating as either fixed route or on-demand. The case study is of the Brooklyn-Queens Connector in New York City using simulation, with results shown in **Figure 2.10**.

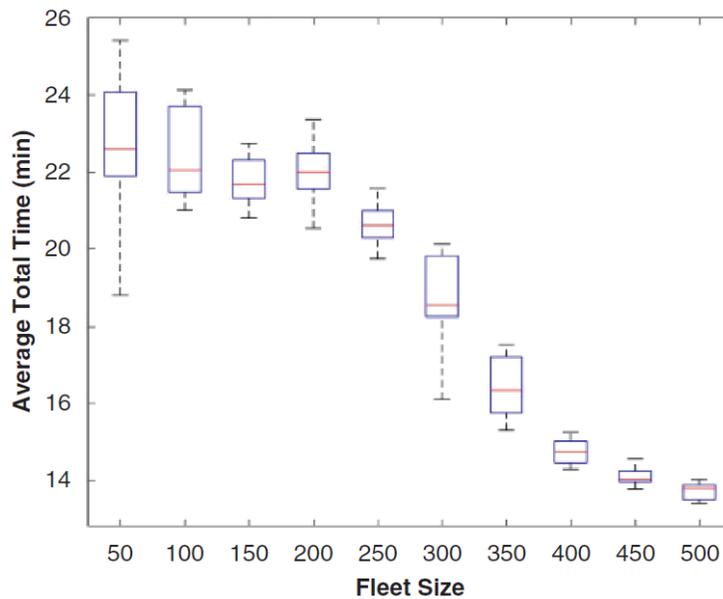


Figure 2.10. BQX study area (left) with fleet size comparison of on-demand SAV (right) (source: Mendes et al., 2017).

In this case study, the BQX was initially designed as a 39-vehicle fleet with 150-person vehicle capacities. The projected average journey times for passengers was around 22 minutes. A simulation of fixed route service using the smaller 10-person capacity EZ-Mile vehicles would not be able to compete in journey times even with a 500-vehicle fleet. On the other hand, operating the service as an on-demand fleet (assuming a simple nearest neighbor heuristic in matching with passengers) could achieve equal or better average journey times with a fleet of 100 or more vehicles.

Section 3: Semi-flexible transit

Prevailing growth patterns and forms of urbanization have resulted in the dispersion of population in many suburban areas and range of demand densities. For the more sparsely distributed demand regions, conventional fixed-route transit service is costly to serve due to the “last mile problem”. Many transportation alternatives have been proposed by researchers and transit planners to improve the degree of flexibility of fixed-route services.

3.1. Typology of flexible transit

As shown in prior sections, the concept of demand-responsive shuttles has existed since the 1970s. However, the popularity of transportation network companies (TNCs) like Uber and Lyft has raised the question of what is possible in personal transportation information technology, and microtransit focuses on how to adapt these tools to the provision of shared rides to the general public in a cost-effective manner.

As with any taxonomy, experts differ on the exact boundaries of the term. Shaheen et al. (2015, 2016a) define microtransit as a privately owned and operated shared transportation system that can offer fixed routes and schedules, as well as flexible routes and on-demand scheduling. Volinski (2019) doesn't limit microtransit to the private sector, defining microtransit as shared public or private sector transportation services that offer fixed or dynamically allocated routes and schedules in response to individual or aggregate consumer demand, using smaller vehicles and capitalizing on widespread mobile GPS and internet connectivity. We go with this latter definition in this study.

Transit planner Jarrett Walker argues that these definitions for microtransit are still consistent with the traditional definitions for flexible transit (Walker, 2018a). Indeed, Koffman (2004) defines flexible transit as transit services that are not pure demand-responsive service (including dial-a-ride and ADA paratransit) or fixed-route service, but that fall somewhere in between these traditional service models. Flexible transit services have some established stop

locations and/or some established schedule, combined with some degree of demand-responsive operation.

Several common characteristics of microtransit are highlighted:

- Publicly available shared rides usually fulfilled on vans or small buses.
- Service ranging from full, curb-to-curb demand-response transportation to flexible fixed-route.
- Uses real-time ridership demand information to dynamically serve trips and relays real-time vehicle location and arrival information to customers.

Flexible transit service provision runs the spectrum from fully customized to flexible route transit. While each service design is unique, we can identify some popular points along the continuum.

- Demand Response Transportation (DRT) picks-up and drops-off customers within a defined service area in response to service requests. In the Microtransit context, DRT is always dynamically scheduled, with wait times ranging from 10 minutes to 45 minutes. Some systems provide curb-to-curb service while others request riders to walk a short distance to an access point. These access points may be predetermined physical stops or dynamically chosen meeting points.
- Flex-Route or deviated fixed-route service is flexible transit anchored to a set of waypoints and time constraints. Urbitran (2006) identifies three typical forms:
 - DRT with a time point at each end of the service area
 - A vehicle running along a route between four or five time points and deviating as necessary for passengers to board and alight.
 - Fixed-route service that allows deviations within a ½ - ¾ mile buffer zone to pick-up and drop-off passengers.

- First-mile, last-mile (FMLM) shuttles strike a balance between flex-route and DRT. Vehicles serve a transit stop according to a defined schedule and boarding at the stop does not require a reservation. The rest of their service area is operated as general DRT, making this a many-to-one (and one-to-many) service pattern. In a strict sense, this can be categorized as flex-route service since vehicles cycle to a specific location on a regular interval. On the other hand, many services that are general DRT operate as first-mile, last-mile for most of their passengers.

The most flexible form of microtransit is on-demand service provided door-to-door or stop-to-stop. In the latter case, the stops are also called “virtual bus stops” because they may not be visited at all. On-demand service is an online implementation of demand-responsive transit (DRT), which solves a classic Dial-A-Ride Problem (DARP) first proposed in the late 1960s (Wilson et al., 1971). DARPs are offline models that determine daily plans dynamically using data provided 24 hours in advance, originally designed to serve people with low mobility (Cordeau and Laporte, 2003). Most current systems of this form are limited to specialized service for older people, people with disabilities, and small communities as paratransit service because they are costly to deploy (Gupta et al., 2010). A study by Rosenbloom (1996) on 40 transit agencies finds that most of them adopted flexible services to remove or reduce the need to provide mandated complementary paratransit service (many of these systems were probably not in conformity with the Americans with Disabilities Act regulations).

In past decades, efforts of serving demand in sparse residential areas have primarily focused on developing various types of flexible transit services. One approach to address the challenges of paratransit is to combine elements of traditional fixed route transit (FRT) service and DRT with an aim to provide flexible route transit service (generally recognized as a cost-efficient alternative to provide curb-to-curb service). **Figure 3.1** provides a simple illustration to show the difference between fixed-route, DRT and flexible route service.

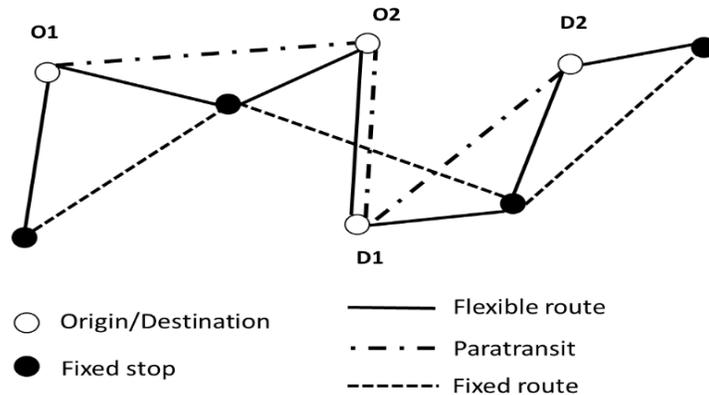


Figure 3.1. Flexible route, paratransit and fixed route services (source: Smith et al, 2003).

A study by Becker et al. (2013) on actual operational data showed that flexible transit services can be more cost-efficient than pure DRT. Koffman (2004) reports several attempts to combine different characteristics of traditional transit and DAR in the same transit system. The report categorizes the semi-flexible transit service into six main types (based on flexible operating policies implemented by different transit agencies throughout North America), illustrated in **Figure 3.2**. In order of increasing flexibility these are:

- *Request stops*: Vehicles operate in conventional fixed-route, fixed-schedule mode. In response to passenger requests, it also serves a limited number of stops near the route. These (optional) stops are located at defined points near the main path.
- *Flexible-route segments*: Vehicles operate in conventional fixed-route, fixed-schedule mode, but switch to demand-responsive operation for a limited portion of the route.
- *Route deviation*: Vehicles operate on a regular schedule along a well-defined path, with or without marked bus stops. It allows deviation to serve demand-responsive requests within a zone around the path. When deviating, vehicles must return on the main path at the exact point where they left to accommodate the deviation. In a case marked stops are present on the path, the vehicle goes back to the path anywhere between the point where it left and the next marked stop. Usually, the width or maximum length of the deviation zone is constrained (may be precisely established or flexible).

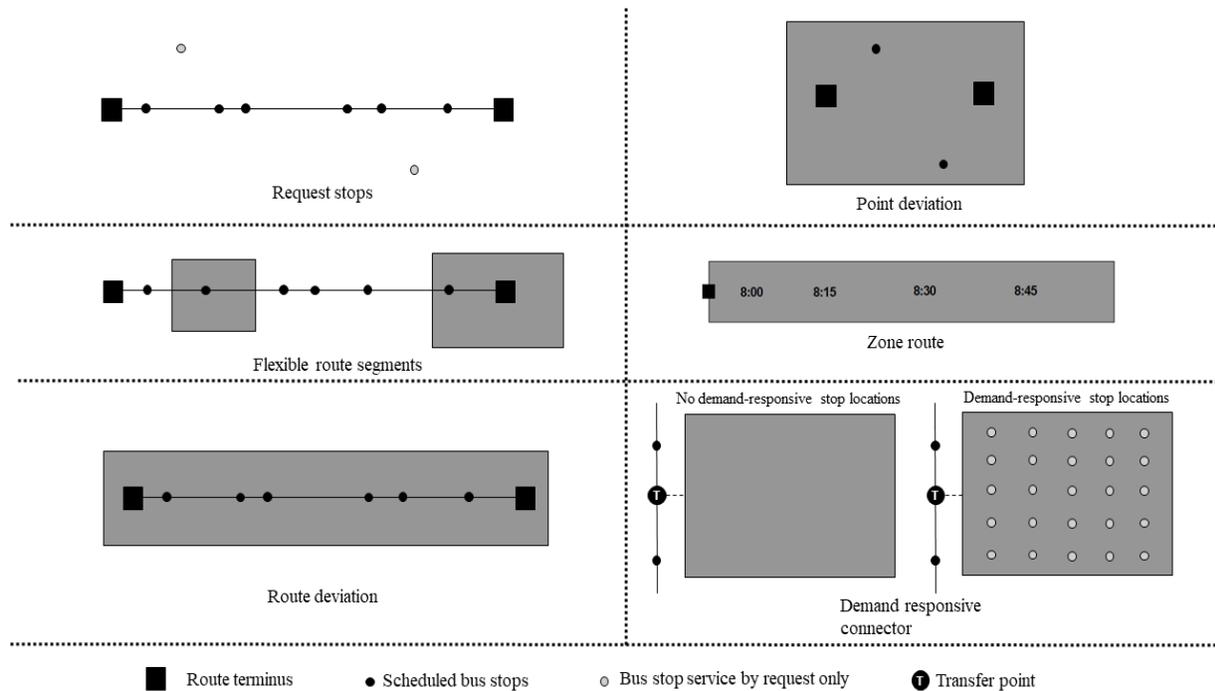


Figure 3.2. Semi-flexible services (source: Koffman, 2004).

- *Point deviation*: Vehicles are not constrained to follow any predefined path. Only a few stops are scheduled, while for the rest of the service, the system serves demand-responsive requests within a zone without any regular path between the stops. Usually, the range of deviations and the service area are defined according to geographical or road network design, or as per the need of the serving neighborhood.
- *Zone routes*: Vehicles operate in demand-responsive mode along a corridor covering a given zone. Usually, they have established departure and arrival times at one or more end points. Departure and end points can be placed at the same location.
- *Demand-responsive connector service (DRC)*: Vehicles operate in demand-responsive mode within a zone. There exists one or more scheduled transfer points that connect with a fixed-route network. The trips to and from the transfer points constitute a high percentage of ridership. This is defined similarly to point deviation service.

An overview of the semi-flexible service classification and methodological issues are presented by Errico et al. (2013). Among the classified flexible services, zone route and DRC are implemented as feeder lines with only one transfer point. Flexible route segments operate in point deviation mode in some portion of the route. Request stops can be considered as a route deviation with allowance for a few deviations. A survey by Potts et al. (2010) reports the percentage of North American transit agencies adopting these semi-flexible systems. Among these, route deviation is the most common form of system (63.9%), whereas zone route accounts for 32.9%, request stops 30.9%, DRC 30.5%, flexible-route segments 19.5% and point deviation 16%. In addition to these, many other systems (sharing similar aspects with DRC) were explored by researchers such as check point dial-a-ride transit (Daganzo, 1984a), Feeder Transit Services (Quadrifoglio and Li, 2009), High Coverage Point-to-Point Transit System (Cortés and Jayakrishnan, 2002), Mobility Allowance Shuttle Transit (Quadrifoglio and Dessouky, 2007), and more recently, demand adaptive paired line hybrid transit (Chen and Nie, 2017).

According to national transit database, demand response (DR) (automobiles, vans, or small buses dispatched by pick up requests and drop-offs at destinations) is the main provider of service in rural and sparsely populated areas (FTA, 2018). DR is the second largest transit service type in the US with twenty-seven thousand vehicles operating during peak service and fifty-five million vehicle revenue hours. Studies found that flexible transit services show promise towards improving travel patterns in low demand areas and revealed the willingness of passengers to use such services (Yu et al., 2017; Frei et al., 2017).

Hickman and Blume (2001a,b) and Häll et al. (2006) studied an Integrated DAR (IDAR) system that allows the user to transfer from DAR vehicle to traditional transit and again to DAR. However, the inconveniences in DAR component contributed to the drawback in the IDAR system.

From an operational point of view, flexible transit services require a decision process to dictate transitions between conventional and flexible service. Maintaining the right balance between operating policies remains a challenge. In view of this, we provide a comprehensive literature review of general modeling frameworks to guide the planning process for flexible transit services. We primarily divide the section into two broad categories: strategic planning and operations, and performance evaluation.

3.2. Strategic planning and operations

This section includes two sub-sections: (i) strategic planning, which includes studies on models proposed to decide the best strategy to choose between fixed and operating policies; (ii) operations required for flexible transit services. **Figure 3.3** shows a flexible route service design presented by Qiu et al. (2014), corresponding to “point deviation” in Koffman (2004).

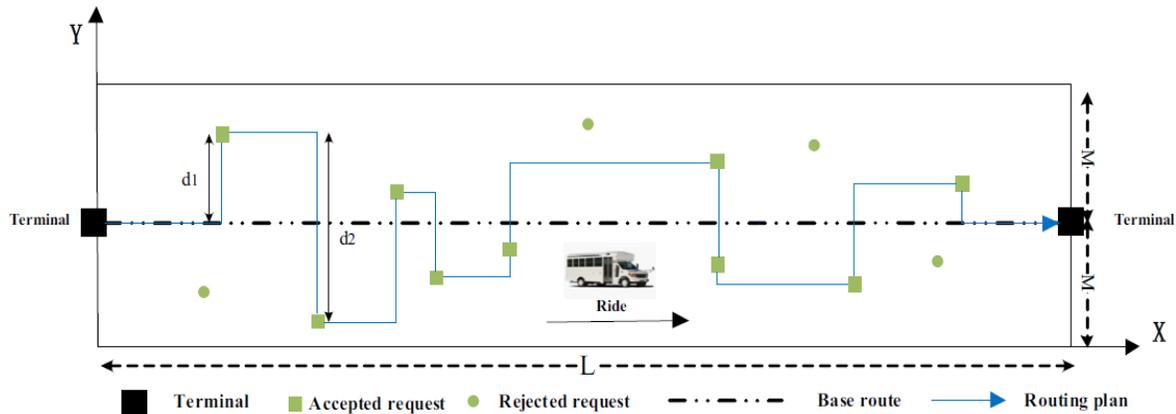


Figure 3.3. Flex route service design (source: Qiu et al., 2014).

3.2.1. Strategic planning

A major concern that arises while deploying a transit service is deciding the type of service suitable for that area. In this context, Daganzo (1984a) considers three possible transit alternatives: traditional FRT, door-to-door dial a ride (DDDART), and checkpoint dial-a-ride (CPDART) to study their cost-effectiveness. CPDART is a combination of DDDART and FRT, where check points are a finite number of locations near trip ends. The author’s goal was to quantify the maximum improvement in efficiency (skipping a few stops, and route shortening where boarding and alighting are absent) by switching from a fixed to check point system.

As CPDART requires a routing strategy, the author first defined a tour over all checkpoints. Once the demand was known, the strategy included skipping the checkpoints (with no requests) to allow vehicles to serve the next in the sequence such that the cost of service plus the travel cost (per passenger) is minimized. The initial sequence was obtained using a Traveling Salesman Problem (the author also explains the variation in expected tour length per different zone shapes considering rectilinear and Euclidean distances (Daganzo, 1984b).

Using an analytical model, the optimal design of FRT and CPDART were derived as the optimal fleet of vehicles and the number of stops per unit area. The study found that only a limited range of demand volume made CPDART more profitable than others (i.e., for intermediate demand levels). For high demand levels, FRT is preferable, since high demand at checkpoints means the system may almost operate on a fixed schedule. As per our knowledge, the CPDART system is considered as the introduction to the integration of fixed route and demand responsive transit system.

Studies by Quadrifoglio and Li (2009, 2010) focus on fixed and DR policies for feeder transit services. These services are similar to DRC, except the transfer stop in feeder transit does not have a predefined schedule and can be visited at any time (depending on number and location of customers to be served). The authors proposed closed-form analytical expressions to estimate the critical demand densities (considered to represent the switching point between competing operating policies). Critical demand densities are functions of geometry of the service area, vehicle speed, walking time, waiting time, and riding time.

The authors also developed analytical and simulation models using an insertion heuristic to decide between the competing operating policies based on maximum service quality (for various customer demands and service zone sizes) (Li and Quadrifoglio, 2010). The goal was to determine the number of service zones in which the service area should be divided for more efficient service. The study found that the critical demand densities for which the FRT and DRC services have an equivalent service quality represent the switching point. The DR policy was found to be preferable during afternoon peak hours and at lower demand rates. The operating environments in both studies consider all door-to-door demands can be accepted and served without considering the constraint of a predetermined *slack time* (when a vehicle operating in an FRT arrives early and has to wait, the amount of additional time allocated between two consecutive scheduled stops is called slack time).

Qiu et al. (2015a) explore the feasibility of replacing FRT with point deviation policies by studying the switching demand densities. A service quality function was developed to measure the performance of transit systems. The authors proposed two criteria (depending on the processing of rejected requests) in the assessment of the service quality function for flexible route services. Based on the occurrence of rejections under varying demand, the service quality can be used to decide on whether to turn to a fixed route policy.

The integration of FRT with point deviation services as a demand-adaptive paired line hybrid transit (DAPL-HT) is proposed by Chen and Nie (2017). This system operates the demand-adaptive service with a stable headway to cover all stops along a paired fixed-route line. This simplifies the complexity of on-demand routing and enables the use of a fleet of smaller vehicles. It also includes a walking zone to allow the system to perform a delicate tradeoff between access and other costs (to increase the design flexibility). The optimal design model is formulated as a mixed integer program. In term of the total system cost, the DAPL-HT outperformed the other two systems under a wide range of demand levels and in various scenarios of input parameters considered in the study.

The integration of demand adaptive services with traditional transit service requires careful planning. In this context, many studies have also addressed the network design problems in the planning of such services. Aldaihani et al. (2004) designed a hybrid grid network that integrated a demand responsive service with fixed-route service. The authors developed algorithms with simple analytical equations to improve the scheduling of such a system. The proposed model determines the optimal number of zones, the number of on-demand vehicles, the number of fixed route lines, and the number of fixed buses in each route that minimizes the total cost (this includes passenger cost, on-demand vehicle cost, and fixed route bus cost).

Errico et al. (2011) presented several aspects of the single-line demand adaptive service design problem (SDDP). The authors examined two hierarchical decomposition approaches to its solution, both made up of a few core problems:

- selection of compulsory stops: defined as the locations which would almost surely be requested for service (although additional compulsory stops can be added).
- a sequencing problem called the General Minimum Latency Problem (GMLP): defined with an objective function that considers a measure of the amount of time the users spend in the vehicle (latency), and
- the problem of defining the time windows, also called the Master Schedule Problem (MSP): given the topological design of a demand adaptive service line (i.e., the compulsory stops, their sequence, and service area segments) and the probability for each demand point to be requested for service, the objective is to determine a set of time windows such that the probability of servicing all issued requests lies within a given threshold, and the total maximum time needed to travel the line is also minimized.

Results showed that by fixing the probability to service all requests, the total time required by a vehicle to complete the service is found to be much higher for small time windows than for large ones. The GMLP (Errico et al., 2017) was formulated as a variant of the Traveling Salesman Problem (TSP). The authors proposed multicommodity-flow based formulation and a branch and cut approach (based on Benders decomposition) to solve it. In addition, they substituted the feasibility cuts (of the classical Benders decomposition) by several classes of valid inequalities (for speeding up computation). Crainic et al. (2012) developed the solution to MSP by studying the scheduling requirements of semi-flexible services. The authors proposed a method to efficiently sample request scenarios to determine the probability distribution of the arrival times at each compulsory stops and the corresponding time windows.

3.2.2. Operations

Most contributions to the operational planning of flexible route transit services employ either continuous approximation or combinatorial methods. Fu (2002) addressed the need for defining optimal slack time allocation required to serve a single rectangle (service area) for a flex-route segment. The model presented is a linear program with an objective to optimize three components: the operator cost, service benefit, and user costs. It reveals the relationship between feasible deviations, slack time, zone size, and dwell time. However, the model does not capture the details of the system behavior.

Considering the same operating environment, but with the addition of vehicles with infinite capacity, Quadrioglio et al. (2006) studied the design of mobility allowance shuttle transit services (MAST). This system has a fixed base route covering a specific geographic zone with one or more mandatory checkpoints at major connections. The deviations are restricted to lie within a service area designed around the base fixed route. The authors developed bounds on the maximum longitudinal velocity of the vehicle to evaluate the minimum threshold values required to be maintained to attract service. Using arguments similar to Fu (2002) and assuming a *no-backtracking policy* (introduced by Daganzo, 1984b), where the vehicle never moves backward with respect to the main direction, the study employed continuous approximations to determine lower and upper bounds. Results showed that the longitudinal velocity of the vehicle is considerably affected by a widening of the service area, but the capacity of the system (customers served per hour) is only marginally influenced. The relationships between velocity and capacity versus demand density can be used in the design

process to set the slack time between checkpoints and other parameters of service (such as headway) of the MAST system.

To compare the results obtained in this study, the authors later performed a simulation, with an operating policy by implementing an insertion heuristic algorithm (Quadrioglio et al., 2007). To enhance the algorithm performance, a set of control parameters were manipulated to reduce the consumption of slack time. The findings gave an approximate relation between the longitudinal velocity and the *service capacity* (i.e., the number of optional locations the vehicle can serve in a given time). The algorithm can be used as an effective method to automate the scheduling of MAST services. Moreover, for static scheduling of such flexible services, a mixed integer program was formulated by Quadrioglio et al. (2008) to minimize the weighted sum of total miles driven by the vehicle, the total ride time, and total waiting time of all customers. The method included sets of logic cuts (inequalities) to speed up the search for optimality (for some instances, this helped reduce up to 90% of the CPU solving time).

Following a similar simplified setting, Zhao and Dessouky (2008) studied the system capacity design of MAST services by analyzing the relationship between service cycle time and the length and width of the service area under the desired *service level* (the probability of arriving at the terminal on-time). The authors simulated a non-backtracking nearest-insertion strategy for the dynamic routing and scheduling process (where a shuttle always runs from one terminal toward another and serves the request that has the nearest horizontal distance ahead of it). It was found that setting the length of the service area to half the travel speed of the shuttle multiplied by the cycle time is an effective approximation. Relations between the dimensions of the service area and the amount of slack time allocated (to provide service flexibility) were studied by Smith et al. (2003). The study considered three possible maximum deviation values (possibly varying for each segment) and two slack time policies (constant for all segments) for route deviation systems. The authors developed a multi-objective nonlinear choice model to maximize feasible deviations and minimize slack time. They provide heuristic solutions to choose the best combination of design parameter values for each of the two objectives.

3.3. System design and performance evaluation

Evaluating the performance of any transit service is necessary in order to improve its operation. Recently, many researchers have investigated the performance evaluation measures of flexible operating policies in the transit system.

Horn (2002) developed a system architecture designed for investigating the performance of public transport systems in which different modes are to be used in combination as a precursor to MaaS, as illustrated in **Figure 3.4**. Even then, solutions were being proposed that involved dynamic transit services like “SmartShuttles”, “RovingBuses”, and “TaxiMulti” (shared taxis). The system called LITRES-2 (architecture shown in **Figure 3.5**), can be used in modeling situations where the critical issues are concerned with the deployment and performance of passenger transport systems rather than the demand side of transportation activity.

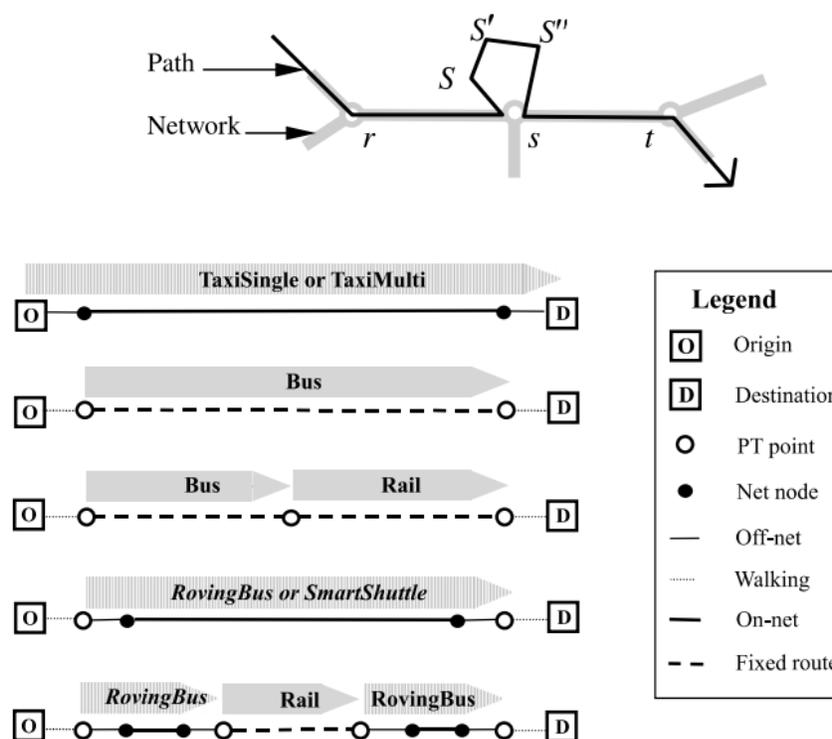


Figure 3.4. Journey structures for a candidate path (source: Horn, 2002).

Sandlin and Anderson (2004) presented a procedure for calculating the serviceability index (SI) to evaluate rural demand-responsive transit system operations. The demand-responsive service capacity was calculated by considering the economic constraints (such as vehicle shortage and overall funding) that affect transit capacity and using them as performance measures. The SI developed incorporates both standard performance measures and specific location variations that can be helpful to evaluate and compare DRT operations.

Crainic et al. (2008) characterize evaluation processes for transit by identifying the two main categories of transportation system planning: stand-alone transit systems, and global (e.g., city or regional) transportation system. The authors presented an evaluation framework for stand-alone transit system with demand adaptive service policy.

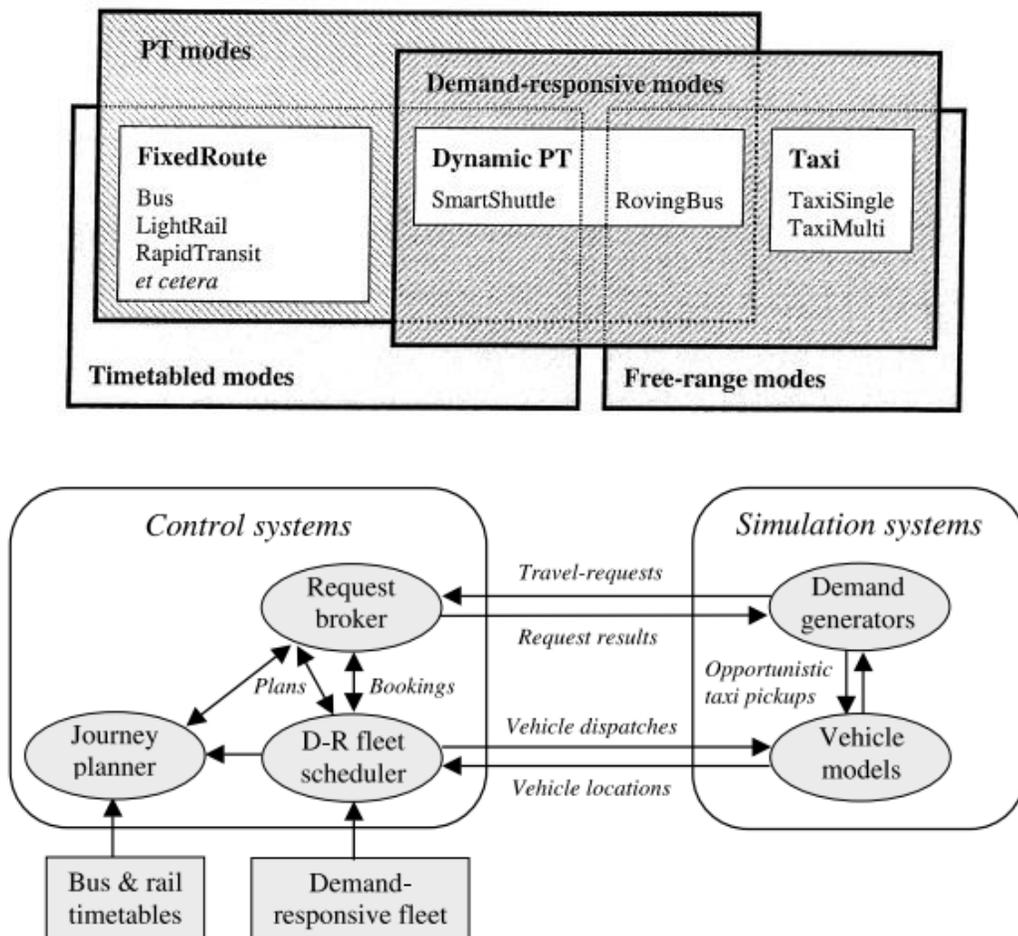


Figure 3.5. (top) Classes of services and (bottom) architecture of control system (source: Horn, 2002).

With an objective to study how the customer's point of view reflects the overall transit performance, Diana et al. (2009) provide a methodology for comparing the performances of FRT and DRT services in terms of distance traveled. Study scenarios were dependent on the road network, service quality level, and demand density. For each scenario, the maximum wait time for DRT was taken equal to double the fixed service headway. The study explains the performance analysis of a public transport service in terms of how its organizational form affects distances traveled (and thus operating costs) for different levels of service quality and demand (in different urban contexts). Findings showed DRT services are more effective than the FRT in minimizing traveled distances when the demand density is not too high and when a good level of service is sought. DRT services performed better in a ring-radial network.

Alshalalfah and Shalaby (2012) investigated the effect of flexible route variables such as the assigned slack time, fixed-stop spacing, operating speed, and on-demand request rate (demand rate and the number of accepted requests) on the performance of flexible route services. The authors explained the importance of an appropriate slack time for effective flexible service. The study showed that increasing fixed stops' spacing increases the number of accepted requests, but more slack time does not necessarily translate into more ridership. Performance improvement (in terms of passenger per vehicle revenue hours) can be achieved only if the ratio of the increase in ridership relative to the added slack time is more than the ratio of the existing ridership relative to the scheduled running time of the original fixed-route. These findings assume that the FRT demand is insensitive to the change of the service to flexible route service and the fixed-stop customers have no option but to use transit.

In Qiu et al. (2014), the proposed strategy showed a reduction in the user cost by up to 30% (without any additional operating cost) when an unexpectedly high travel demand surpassed the designed service capacity of flexible services. Findings suggest that an improvement of service quality via the dynamic station strategy could be more remarkable under extreme operating surroundings (e.g., when the area width or the walking time weight is higher).

Using a similar strategy as above, the authors proposed a demi-flexible transit operating policy and studied its performance evaluation at expected and unexpected demand levels (Qiu et al., 2015b). In this system, the policies do not provide complete curb-to-curb services, but still offer some degree of flexibility. The most common form of services in this category is the flag-stop operating policy, where users may request for service at any point of the main path, or at marked stops, by waving their hand when the vehicle approaches (this can be found in many

transit systems in rural and suburban areas). The authors explored the advantages of demi-flexible operating policies in promoting public transit services in low-demand areas.

Section 4: On-demand microtransit

Beyond fixed route transit and flexible route microtransit, the third category of service covered in this compendium is on-demand microtransit. This is the most flexible service type that is typically most operationally costly but also can reduce user costs when user demand is sufficiently low density. The section discusses service evaluation methods, then covers some of the advances in static DARP and real time (dynamic) DARP before providing some real-world examples of microtransit services.

4.1. Service evaluation

On-demand microtransit started as offline DRT to solve DARP. The first DARP models were proposed by Wilson (1967), although structural properties of tours on a plane were already being studied by the likes of Beardwood et al. (1959). The optimization of a service problem like DARP has been found to be computationally intractable (NP-hard) because it is a generalized case of a traveling salesman problem (TSP) which is also NP-hard (Papadimitriou and Steiglitz, 1977). As a result, evaluation of different routing-based service designs cannot be done in a straightforward manner of solving an optimization model. Instead, evaluation is done for specific policies, often using continuous approximation models for scalability.

4.1.1. General on-demand service designs

Stein (1978) proved that the length of an optimal tour to serve n passengers approaches a certain bound as the $n \rightarrow \infty$, as shown in Eq. (3.1), where Y_n is the optimal tour length of a single bus randomly picking up and dropping off passengers distributed uniformly over a region R with area a with an absolute constant b (found to be around 0.75).

$$\lim_{n \rightarrow \infty} \frac{Y_n}{\sqrt{n}} = \frac{4}{3} \sqrt{2} b \sqrt{a} \approx 1.89 b \sqrt{a} \quad (3.1)$$

When several buses are available, the length of the tour is simply divided by the number of buses.

Daganzo et al. (1977) derived a many-to-one DRT system while Daganzo (1978) examined a many-to-many DRT system under different operating policies. The latter is studied as a queueing network as shown in **Figure 4.1**. Modeled as such, for simple operating policies like having travelers arrive randomly in a region and a bus either routing to the nearest feasible point or alternating between pickups and drop-offs can be evaluated analytically.

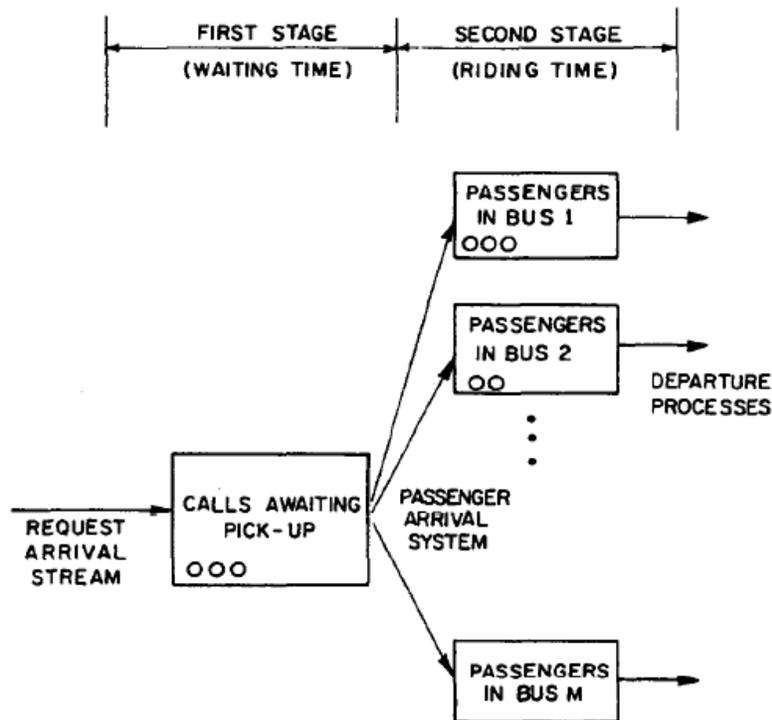


Figure 4.1. A many-to-many dial-a-bus as a queueing network (source: Daganzo, 1978).

A few other contributions have been made in this area. Psaraftis (1983) evaluates a heuristic for many-to-many DARP. Daganzo (1987) considers time windows using “time bins” which may not handle tight time constraints well. Diana et al. (2006) derive probabilistic expressions for serving a large-scale system of pickups and drop-offs with tight time window constraints. Stop spacing for on-demand public bus service is modeled by Zhang et al. (2019), in which operators have perfect traveler origin destination in advance and can schedule satisfactory service accordingly.

A recent study by Daganzo and Ouyang (2019) provides a general analytic framework to model transit systems that provide door-to-door services (their work encompasses non-shared taxi, paratransit, and ridesharing, as illustrated in **Figure 1.5**). The modeling is based on systematic quantification of cost and performance in approximate closed-form formulas. For the conventional transit system, the authors assume that the routes form a uniform square grid over a square region where the vehicle fleet is evenly distributed across all routes, the transfer and station dwell times are negligible, and the passengers' walking speed is 1/10 of the vehicle speed. It is found that the fleet size needed to achieve a specific door-to-door travel time standard increases with increase in demand.

The findings suggest that bigger and denser cities provide a more favorable environment for conventional transit. By comparing the analytical results with agent-based simulations, the authors consider shifting of fleet curves (in the case of taxis) in order to account for errors that are not captured by an analytical model. The study provides valuable insights that could be used by taxi companies and government agencies to systematically explore different operating, pricing and regulatory strategies and understand how a system might respond to such regulations.

4.1.2. Last mile on-demand service

A subset of research is conducted on feeder systems to address the “last mile problem” in transit. The problem can be illustrated with **Figure 4.2**.

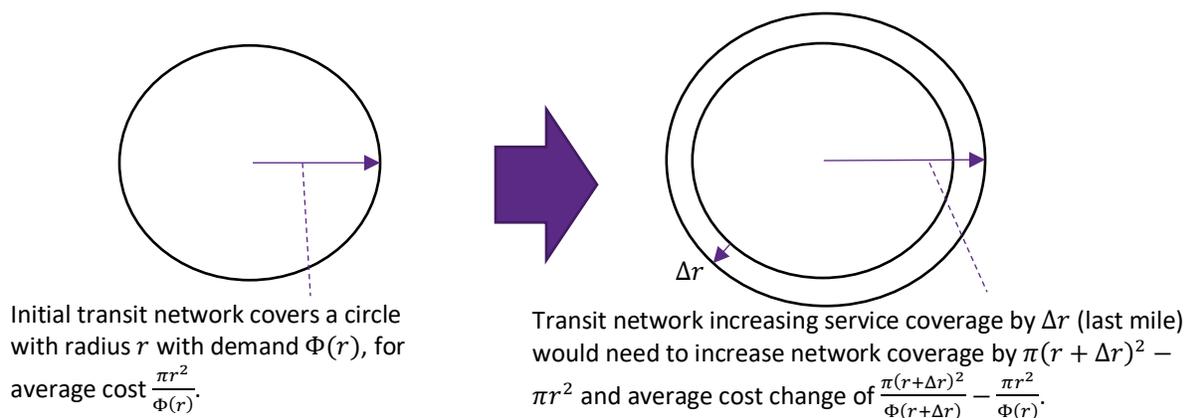


Figure 4.2. Illustration of transit service coverage last mile problem.

Each additional mile that a system wishes to cover beyond a central core requires quadratic increases in costs to serve. Meanwhile, if demand density depreciates from the core similar to a Normal distribution with the mean at the core, the effect of demand to operating cost is compounded. For example, if demand in the initial network is described by a cumulative distribution $\Phi(r)$, the average cost would be $\frac{\pi r^2}{\Phi(r)}$. Increasing by Δr would result in a change to average cost of $\frac{\pi(r+\Delta r)^2}{\Phi(r+\Delta r)} - \frac{\pi r^2}{\Phi(r)}$, where $\frac{\pi(r+\Delta r)^2}{\pi r^2} > \frac{\Phi(r+\Delta r)}{\Phi(r)}$. To tackle this, transit networks have been shown to benefit from using mainline and feeder systems in hub and spoke structures.

Chang and Schonfeld (1991a,b) first compare the relative advantages of fixed route and DRT systems as feeder services as shown in **Figure 4.3** and identify a similar demand density threshold under which DRT is more cost effective.

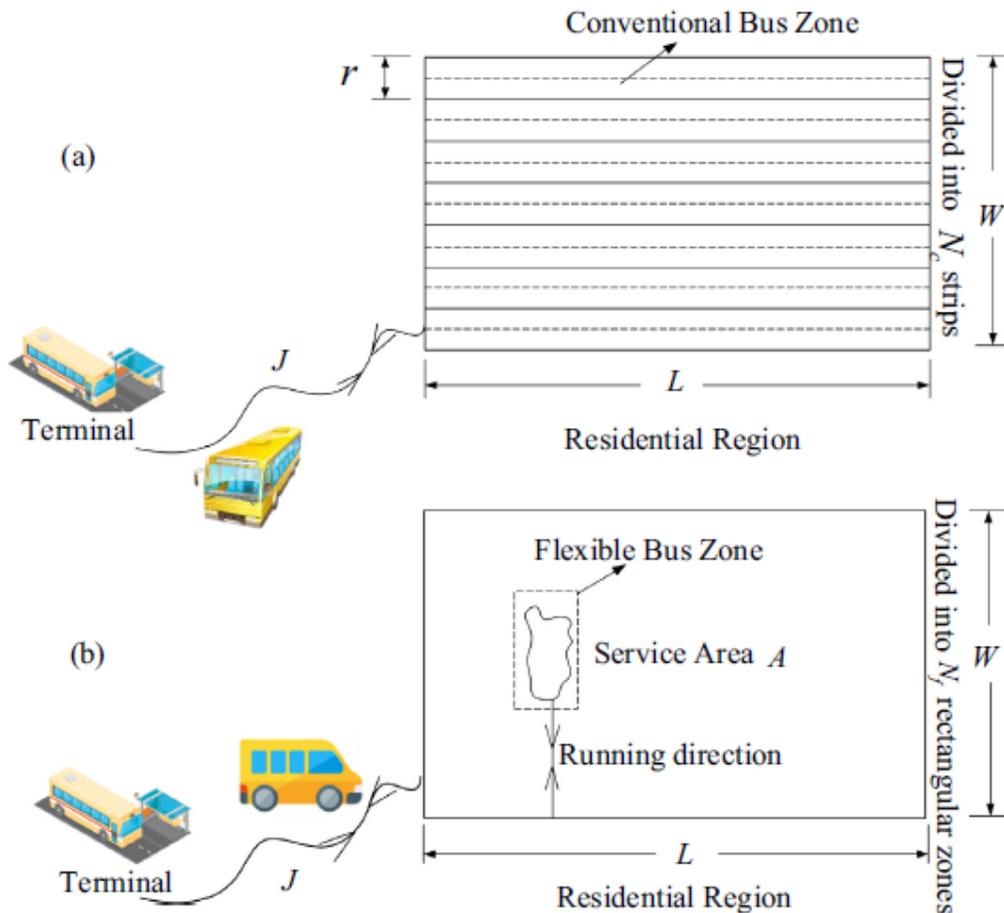


Figure 4.3. (a) Fixed route and (b) on-demand feeder services (source: Guo et al., 2018).

For both the services, the study assumed that the buses either collect passengers from a local service area or distribute passengers to a local area in relation to a terminal station (many-to-one distribution). The average cost per trip is used as a criterion to determine the preferable system, with decision variables being fleet of vehicles, route spacing (for FRT), and service zone size (for flexible route system). They show that for smaller service areas, higher express speeds, lower in-vehicle times, or higher access and wait times, flexible bus system becomes more advantageous. Higher operator cost and lower user cost are observed for flexible bus system compared to FRT (operators may choose to provide FRT at demand densities where total costs favor flexible system). It also justifies higher subsidies for flexible route system due to lower user costs.

Kim and Schonfeld (2012) improve these optimization models for analyzing and integrating fixed route and on-demand last mile services. The authors optimize the flexible service headways (instead of just using maximum allowable headways) and introduce directional demand split factors in their study. These models are used to compare between different transit services as demand changes over time employing one terminal in a single local region. As an improvement to this study, Kim and Schonfeld (2013) explore the concept of Mixed Fleet Variable Type Bus Operation (MFV) in multiple regions (i.e., integration of service types and fleets jointly). The model is formulated as a nonlinear mixed integer problem and solved using a hybrid solution approach that combines an Integer Genetic Algorithm (IGA) and analytic optimization. They also study the benefits of sharing mixed bus fleets (i.e., vehicles of different sizes) among regions and time periods.

Kim and Schonfeld (2014) explore integrating conventional and flexible bus services for potential reduction in system cost. Probabilistic models were developed to optimize the delay and cost savings achieved from the coordination of services. Results suggest that timed transfers are desirable for increasing the probability of vehicle connections at transfer terminals, thereby minimizing passenger wait times compared to uncoordinated operations. The proposed models can be used to determine when various integration and coordination options are and to quantify their effects on service levels, costs and other measures of effectiveness.

While many studies focused on one region or one time period, Kim and Schonfeld (2015) study systems with multiple dissimilar regions and periods. The authors propose a mixed integer nonlinear welfare maximization problem for FRT and flexible route services. The goal is to compare optimized net benefits of two services, with constraints on capacities and subsidies.

A real-coded genetic algorithm is used to optimize variables (service type, zone sizes, headways, and fares) and to determine the maximum welfare threshold between two services.

Chandra and Quadrifoglio (2013) develop an analytic model using Stein's (1978) formula to estimate the optimal terminal-to-terminal cycle length of a demand responsive feeder for the maximum *service quality* (defined as the inverse of a weighted sum of waiting and riding time). They consider the operations as a queueing problem with waiting time and in-vehicle time in the objective function (but not operating cost). Particularly, the model is designed for a vehicle within a rectangular service area and without a line-haul segment beyond that service area. However, their study is limited to analyzing cycle lengths of flexible transit services (to decide the dispatch policy) without seeking to coordinate/integrate FRT and flexible services.

The pricing of urban transportation systems also serves as a performance measure and has been studied in diverse contexts. In the context of flexible transit service, recent works by Chen and Wang (2018a,b) focus on last mile transportation service (LMTS) pricing from an operational perspective and provide efficient strategies for passenger assignment, vehicle routing and scheduling based on a set of last-mile demand information. The authors propose a constrained non-linear optimization model with an objective to maximize social welfare. Two fairness guarantees are considered for this purpose: price discount and service priority (applied to special-type passengers with higher service valuation but lower waiting time disutility). Results show significant gain in optimal social welfare by LMTS implementation (using real data from Singapore). It is seen that price discounts for special groups have almost no effect on social welfare but consumer surplus for passengers in those groups suffers significantly.

4.2. Service design

While the focus on this compendium is not on specific routing optimization models (of which there are too many and would be out of scope), there are some interesting variations to the problem that consider alternative structures or ways to mix service or structural types. An overview of such variations based on offline dial-a-ride is first provided, followed by one for real time routing.

4.2.1. Offline dial-a-ride

A generalization of DARP, called Integrated Dial-a-Ride (IDARP), was developed by Häll et al. (2009). The main difference between the IDARP and DARP is that the users in IDARP may change mode at transfer points and then travel a specified distance with public transport (fixed route service). In this case, when the passenger is carried to a transfer node via dial-a-ride service, it uses the fixed route service to travel to another transfer node where the passenger is picked up by another vehicle in the fleet of dial-a-ride vehicles and is dropped off at the respective destination. By using the existing fixed route service the DRT operators can reduce their operating costs. The IDARP shares similarity in many aspects with the pickup and delivery problem with transshipments and the DARP with transfers (Cortes et al., 2010; Rais et al., 2013; Masson et al., 2013).

The formulation is based on the directed graph formulation of the DARP (Cordeau, 2006) with an expansion that schedules both vehicle and customer itineraries. In the directed graph $G = (N, A)$, N is the set of all nodes, including pick-up nodes, drop-off nodes, depot nodes and transfer nodes, and A is the set of arcs connecting the nodes. Each arc has an associated cost and travel time. The objective in the model is to minimize the total routing of the dial-a-ride vehicles (addressed from the operator's perspective). Due to the design of the network, the problem size increases very quickly with the number of requested trips as well as with the number of transfer locations included. Hence, to counteract this rapid increase in problem size, the authors consider different methods to strengthen the proposed (arc-based) model.

Posada et al. (2017) extend the IDARP to include timetables for the fixed route services, forcing the fleet of vehicles to schedule the arrival at the transfer locations. The authors present two mixed integer linear programming formulations (MILP) of the integrated dial-a-ride problem with timetables (IDARP-TT). These formulations differ in the way the transfers are modeled. The study focuses on the issues related to practical implementation of IDARP, e.g. lower levels of service due to transfers, delays, and adaptation costs. The objective is to find vehicle routes which minimize the combined operational costs of the DRS and the fixed route service. In the proposed models, a fleet of heterogeneous demand responsive vehicles with different speeds, operational costs, and capacities is introduced. The fleet is divided into different vehicle classes such that the vehicles within each class are homogeneous.

The first model of IDARP-TT (Model 1) retains the basic transfer node structure of the IDARP model (Häll et al., 2009). The problem size in Model 1 grows very quickly as a function of the

number of requests. This effect is diminished in the second model (Model 2); instead of allowing each request to have a specific node at each transfer location, the model includes nodes representing every visit to that specific transfer location. Therefore, several requests can use the same transfer node and all transfer nodes can be used by all requests. This opens up for a location being visited multiple times which significantly reduces the number of binary variables needed in the IDARP-TT. The strengthening of the models is done using arc elimination and with additional sets of constraints. The findings from both theoretical calculations and computational experiments indicate that Model 2 outperforms Model 1.

4.2.2. Real-time routing

Real-time, or dynamic or online, routing has a long history from the late 1970s (Psaraftis, 1980; Psaraftis, 1995; Madsen et al., 1995; Agatz et al., 2011; Hosni et al., 2014). Real-time operating policies are divided into myopic and non-myopic policies: a non-myopic policy considers cumulative costs over a time horizon by using lookahead or other types of approximation. Some strategies used to overcome challenges in service design are described as follows.

One example variant involves constraining the service to consider hubs and single transfers. Cortés and Jayakrishnan (2002) propose a real time routing service called “High Coverage Point to Point Transit” (HCPPT) where each transit hub is designed for a group/cluster of such cells. Each transit vehicle is assigned to a home area where it has a reroutable portion of its trip in a given cell and has a non-reroutable portion of travel on a trunk line to a given neighboring hub (to which it is assigned). A passenger can be dropped off at the adjacent area hub where they may then travel to their final destination on another reroutable vehicle. This design strictly eliminates more than one transfer for any passenger and significantly decreases waiting time. The scheme is characterized by its large fleet of smaller vehicles, lower fares, passenger pooling to improve vehicle occupancy, and use of IT (Internet, GPS). Findings showed considerable improvement over previous DRT system implementations, considering the level-of-service and ride time indexes. This work has been expanded upon by Jung and Jayakrishnan (2011) and illustrated in **Figure 4.4**.

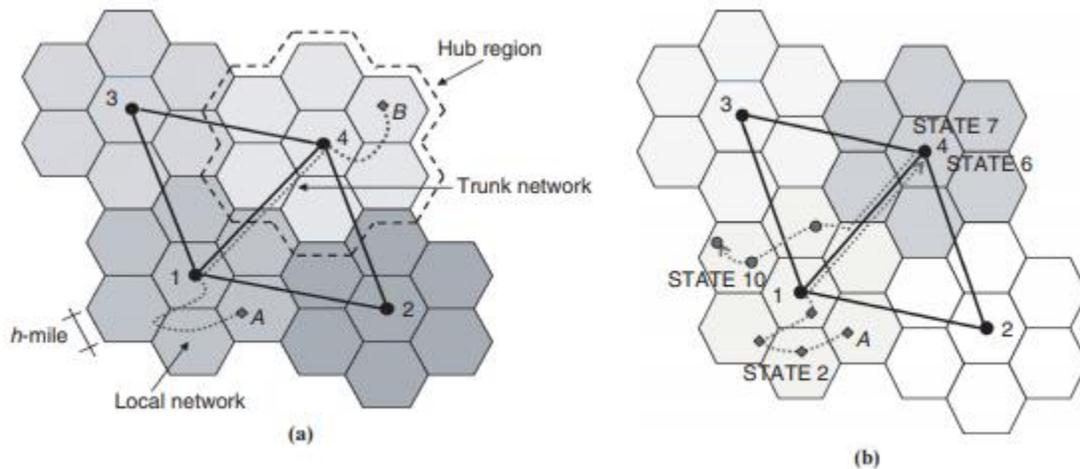


Figure 4.4. HCPPT scheme with (a) passenger trip and (b) vehicle schedule (source: Jung and Jayakrishnan, 2011).

Another variant uses queueing theory to approximate the lookahead costs for making routing decisions, as exemplified by Pavone et al. (2010) (queueing network), Hyytiä et al. (2012) (online DARP), Sayarshad and Chow (2015, 2017) (online DARP with queue tolling, and relocation). Conceptually, each vehicle becomes a server for which the cost function is updated to include queueing delay as illustrated in **Figure 4.5**.

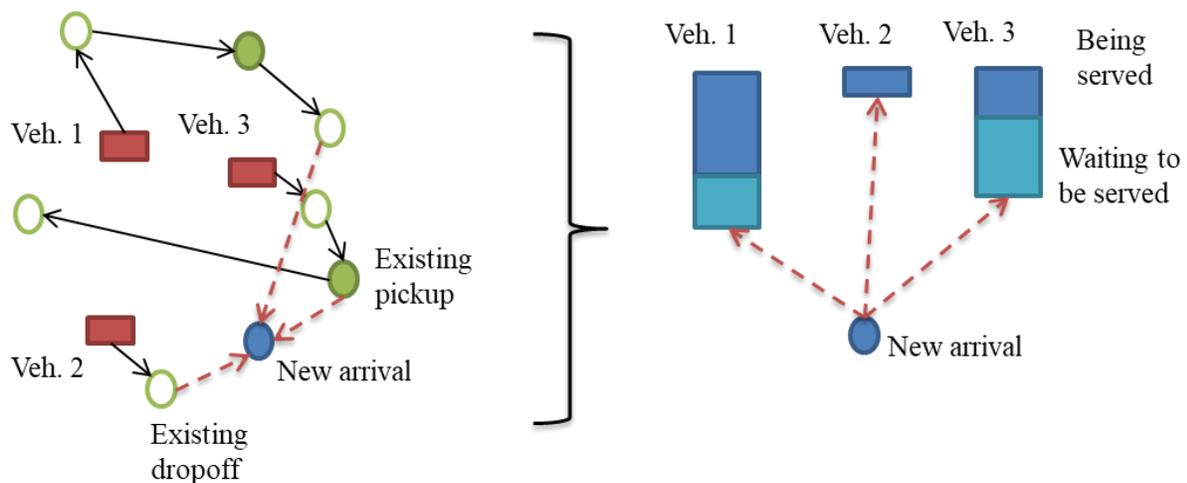


Figure 4.5. Illustration of look-ahead approximation using queueing (source: Sayarshad and Chow, 2015).

The use of real time routing with queueing and connection with public transit network as a mainline was proposed by Ma et al. (2019), essentially an online operation of IDARP. The algorithm was tested for travel demand in Long Island to compare the costs of operating a microtransit service versus an online IDARP service. **Figure 4.6** illustrates the difference in trip distances made, where significant savings can be observed going from (a) to (b).

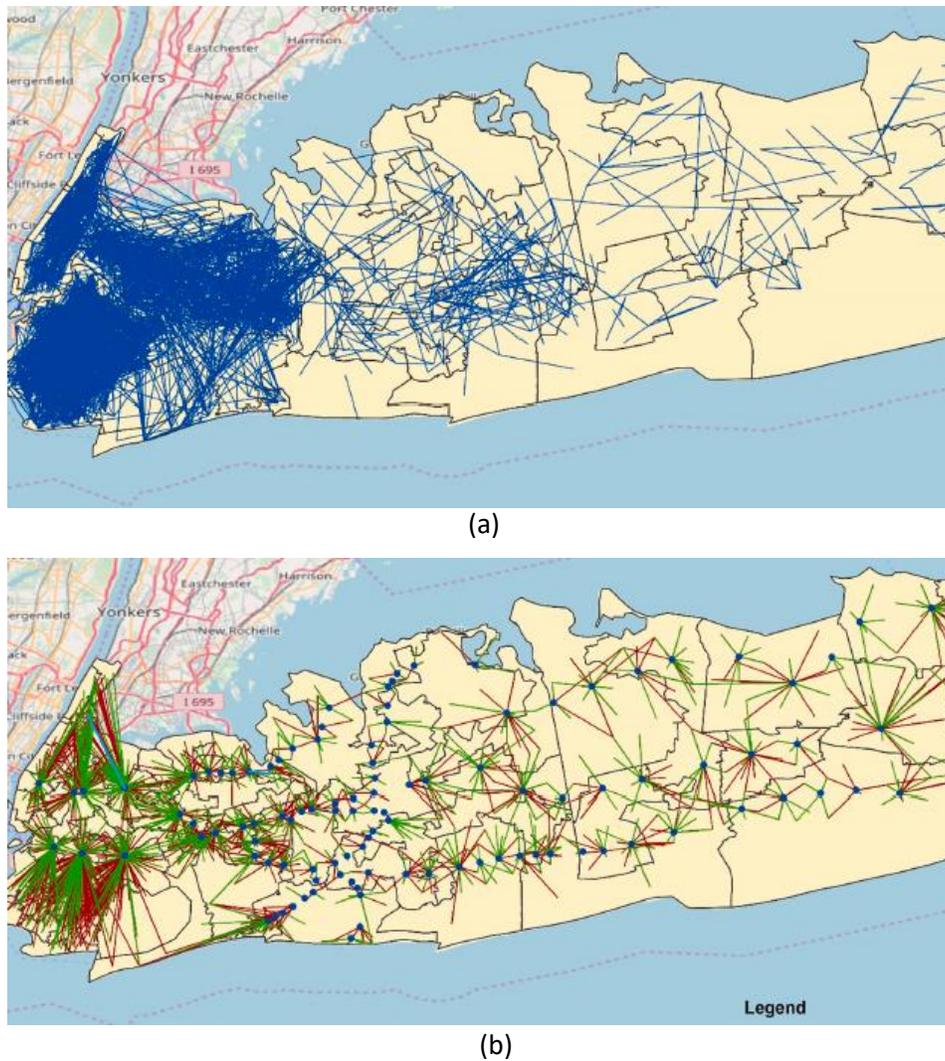


Figure 4.6. Trip lengths made under (a) shared taxi only versus (b) shared taxi and LIRR (source: Ma et al., 2019).

Another important development to on-demand microtransit is the consideration of “meeting points” or virtual bus stops. Instead of picking up and dropping passengers off at their

stated locations, the system would consider assigning them to common meeting points that may be a few blocks away. Stiglic et al. (2015) show that such a system can improve matching rate and lead to mileage savings. Rasulkhani and Chow (2019) discuss how this can be viewed as a cost allocation between users and the operator(s) and identify the improvement in operating cost improvement needed to justify a 1-block detour for travelers. Chen et al. (2019) formulate a mixed integer program to solve a ridesharing problem with meeting points for employees of companies that agree to share the calendars of their employees.

The design of a cost sharing mechanism for DRT systems need to consider a fare structure such that all its potential passengers are treated fairly. This requires DRT to make instantaneous and irreversible decisions despite having no knowledge of future ride request submissions. To address this issue, Furuhata et al. (2015) propose a novel cost sharing mechanism called proportional online cost sharing (POCS). Mainly two cost sharing mechanisms are used in DRT systems i.e., proportional cost sharing (passengers with higher demand or ride requests contribute more toward the total cost), and incremental cost sharing (shared cost of each passenger is its marginal cost that is the increase in total cost due to its request submission). POCS is found to overcome the shortcomings of these mechanisms in an online setting by satisfying the following five desirable properties of online transport systems (which is attractive to both transport providers and passengers):

1. *Online fairness*: The shared cost per alpha value (which is the number of transport resources a passenger requests) are never higher than those of passengers who submit their requests for a ride after them.
2. *Immediate response*: Passengers receive (ideally low) upper bounds on their shared costs at any future time immediately after their ride request submissions.
3. *Individual rationality*: The shared costs of passengers accepting their fare quotes never exceeded their fare limits at any future time.
4. *Budget balance*: The operating cost (considered as the total cost) is equal to the sum of the shared cost of all passengers. Thus, no profit is made, and no subsidies are required.
5. *Ex-post incentive compatibility*: The best strategy of any passenger is to submit its ride request truthfully (provided that all other passengers do not change their submit times

and whether they accept or decline their fare quotes), because fares per mile of requested travel is never higher than those of passengers who submit their ride requests after them i.e., the shared cost cannot be decreased by delaying the ride request submission.

Since the DRT systems need to calculate the minimum operating cost after each ride request submission, the authors also presented an experimental study (with a transport simulation) using heuristics to compute a low operating cost (not guaranteed to be minimal). With POCS, passengers would have no uncertainty of whether they can be served or about the highest fare of the service. Findings showed that POCS allows DRT systems more time to find routing solutions to offer lower fares to subsequent passengers (due to synergies with the early ride requests), thereby allowing service to more passengers.

4.3. Real world examples

Microtransit-like service in North America dates back to the 1970s, when transit agencies were looking for ways to reduce congestion and energy consumption (Higgins, 1976). Some of the most successful systems operated in the greater San Diego metro area. Higgins recounts the success of the El Cajon Express, a taxi-operated demand response dial-a-ride system available to the general public. At its peak popularity it served 8 passenger trips per vehicle hour of service, but once San Diego streetcar service was extended to the region, ridership waned. By the late 1990s the service was targeted for elimination (Cervero, 1997).

El Cajon Express and other systems of its type were available on an on-demand basis by calling ahead, and a professional scheduler would manually match trip requests to vehicles. While the first computer scheduled dial-a-ride systems were implemented during this same period, they were unable to field dynamic requests and the benefits compared to manual scheduling were negligible for small systems (Newman et al., 1981).

Koffman (2004) surveys transit agencies that have developed flexible transit options. Winnipeg's DART demand response service is a notable example included as a case study. With a waypoint DRT with scheduled pickups at transit points timed to coincide with bus arrivals,

DART was designed to replace fixed route service during low demand periods during nights and weekends. The service area had several fixed stops where passengers can be picked up or dropped off. Despite this relatively open structure, most trips begin at a transit point and thus are not scheduled. Riders simply board the vehicle, inform the driver of their destination, and the driver manually routes the requests using a sheet like the one shown below in **Figure 4.7**. In 2002, DART averaged 7.3 passengers per vehicle revenue hour, and is still operating under the same service pattern as of the writing of this report.

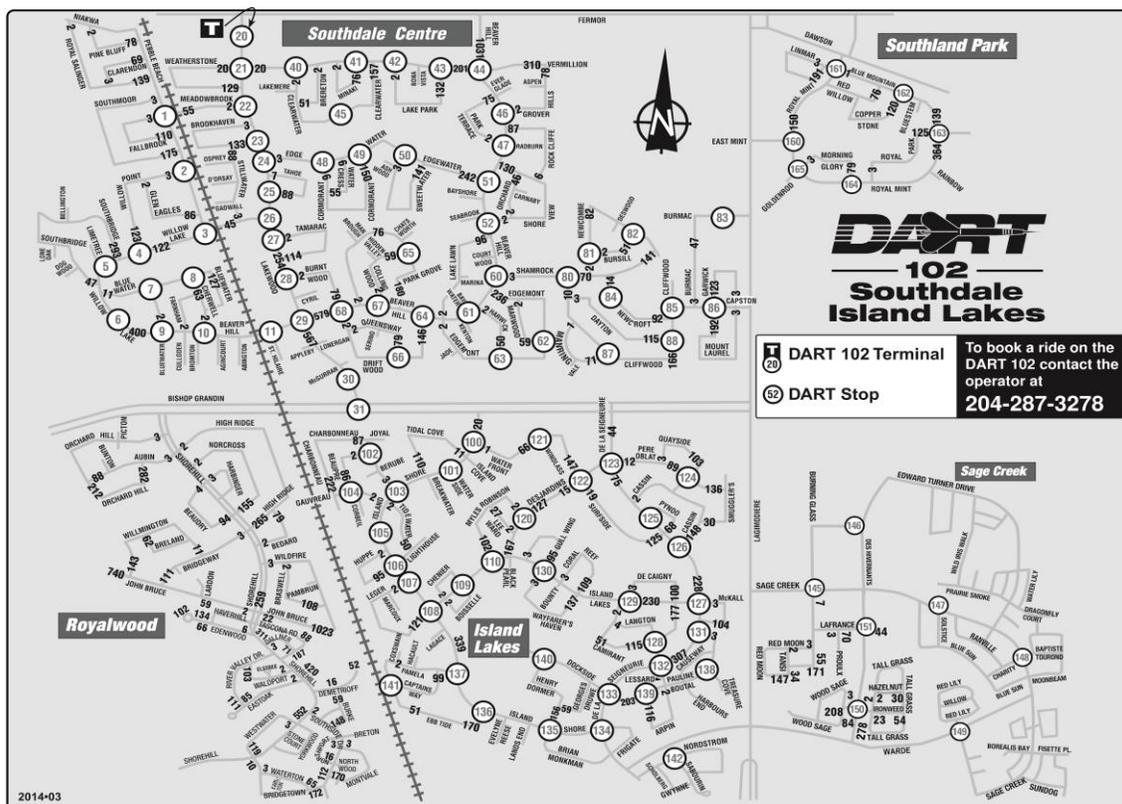


Figure 4.7. Winnipeg Transit DART service area with available stops marked by circles (source: Koffman, 2004).

Denver’s Regional Transportation District (RTD) is regarded as a national leader in demand-response service, with Volinski (2019) saying “No other transit agency in the nation has embraced the provision of general public DRT as much as RTD has.” RTD’s DRT offerings, now known as FlexRide, include both first mile/last mile (FMLM) connections to regional transit and

zoned community circulators. In 2017, the average overall productivity for the routes was 3.8 pickups per vehicle hour, although some FMLM services achieved relatively high productivity of between 7 and 8 pickups per vehicle hour (see **Figure 4.8**). After a 2019 rebrand, the new FlexRide service was relaunched with a new web app that was designed to reduce advance request times from 60 minutes down to 10 minutes, making service competitive with shared TNC rides for a \$3 flat fare. This is an example of how the best examples of public DRT have converged to the technological standards of modern microtransit.

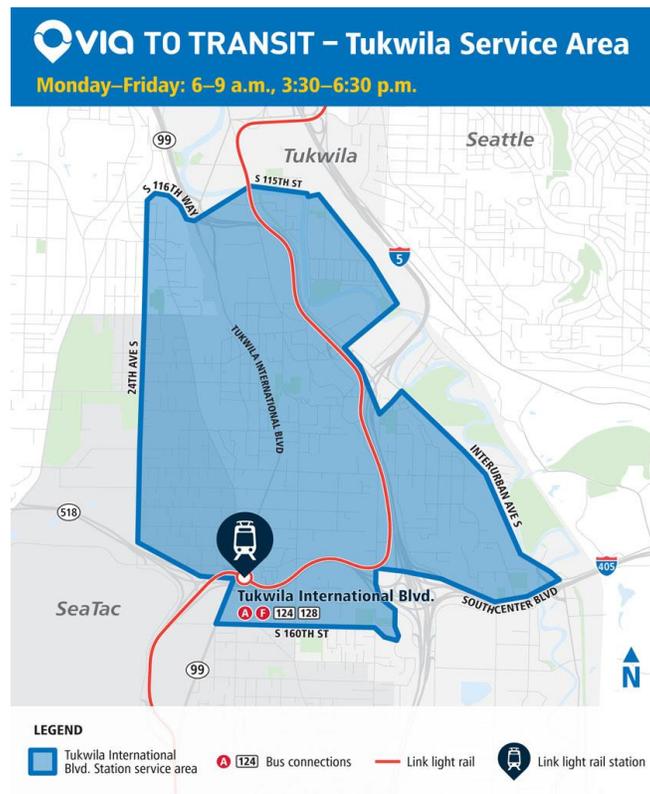


Figure 4.8. Via to Transit Tukwila service area, an example of FMLM microtransit service (source: King County, 2019).

Several other systems have been shown in **Figure 1.3**. A list of more examples are highlighted in **Table 4.1**.

Kutsuplus in Finland is one of the first systems that could be thought of as a new, technology-enabled microtransit DRT service from the start. Launched in 2012 in the Helsinki

capital region, Kutsuplus offered users differentially priced and timed shared rides based on their requests, one of the earliest examples of such a dynamic pricing and trip routing system in practice (Jokinen et al., 2019).

Table 4.1. Example real-world microtransit systems

Service	Location	Service Type	Year Introduced	Vehicle Operation	Technology provider	Productivity (pax/veh-hr)	Fare box Recovery
Via to Transit	King County, WA	First Mile Last Mile	2019	Private Contractor	Via		
Smart Ride	Sacramento, CA	General Public DRT	2018	Public Transit Agency	TransLoc	3.6	
Neighbor Link	Orlando, FL	General Public DRT	2017	Private Contractor	Trapeze PASS	3.3	5%
Arlington on Demand	Arlington, TX	General Public DRT	2017	Private Contractor	Via	3.1	30%
AC Transit Flex	Alameda County, CA	First Mile Last Mile	2016	Public Transit Agency	Demand Trans	3.1	
VTA FLEX	San Jose, CA	General Public DRT	2016	Public Transit Agency	RideCell	0.4	
Bridj	Kansas City	General Public DRT	2016	Private Contractor	Bridj	0.1	
Cherriots West Salem Connector	Salem, OR	First Mile Last Mile	2015	Private Contractor	Demand Trans	3.3	
Acres Homes Community Connector	Houston, TX	General Public DRT	2015	Public Transit Agency	Trapeze PASS	2.5	
Via	New York, NY	General Public DRT	2014	Private Company	Via		
Kutsuplus	Helsinki, Finland	General Public DRT	2012	Public Transit Agency	Ajelo	2	14%
Call-n-Ride/ FlexRide	Denver, CO	General Public DRT, First Mile Last Mile	2000	Private Contractor	Demand Trans	3.7	7%

FLEX	Minneapolis Suburbs	Flex Route	1998	Private Contractor		4.9	
DART	Winnipeg, Canada	First Mile Last Mile	1996	Public Transit Agency		7.3	
OmniRide	Dale City, VA	Flex Route	1995	Public Ind. Service		8.7	
The Ride Solution	Palatka, FL	Flex Route	1988	County Transportation Coordinator		2.4	
El Cajon Express	El Cajon, CA	General Public DRT	1973	Private Contractor	Yellow Taxi	8	30%

Haglund et al. (2019) use a multidimensional evaluation framework on Kutsuplus to evaluate the financing and pricing policy, and users' and non-users' perceptions about the implemented service. The study focuses on the analysis of completed user journeys, accounting for Kutsuplus operating area, timing, and pricing scheme. The findings from the framework used in the study provides a range of implications for user-centric service design of DRS systems integrating the interdependencies between operating scheme, service pricing, and service level by alternative transport models. The framework included the following performance evaluation dimensions: aggregate operation statistics, spatio-temporal variations, journey variations by user age group, and journey duration comparison. Results show increasing demand for Kutsuplus over time; the hourly demand pattern for Kutsuplus had a similar shape to the fixed public transport demand pattern, with small differences in peak time start and duration. The journey data distributions show that most of the users were 30 to 65 years old, and most Kutsuplus journeys were less than 10 km long, with duration less than 30 min, cost under €10, and had low wait time after journey offer acceptance. Despite a vehicle capacity of nine seats, the average user occupancy was 1.27; such low vehicle occupancy highlighted an important weakness in the system operation. One of the explicit goals of the Kutsuplus program was to woo private car owners into shared transportation in order to decrease congestion. After three years the funding required to sustain the program was deemed unsustainable, and Kutsuplus

suspended operations in 2015 with an overall farebox recovery of 14%. **Figure 4.9** shows the vehicle productivity and trips taken over time.

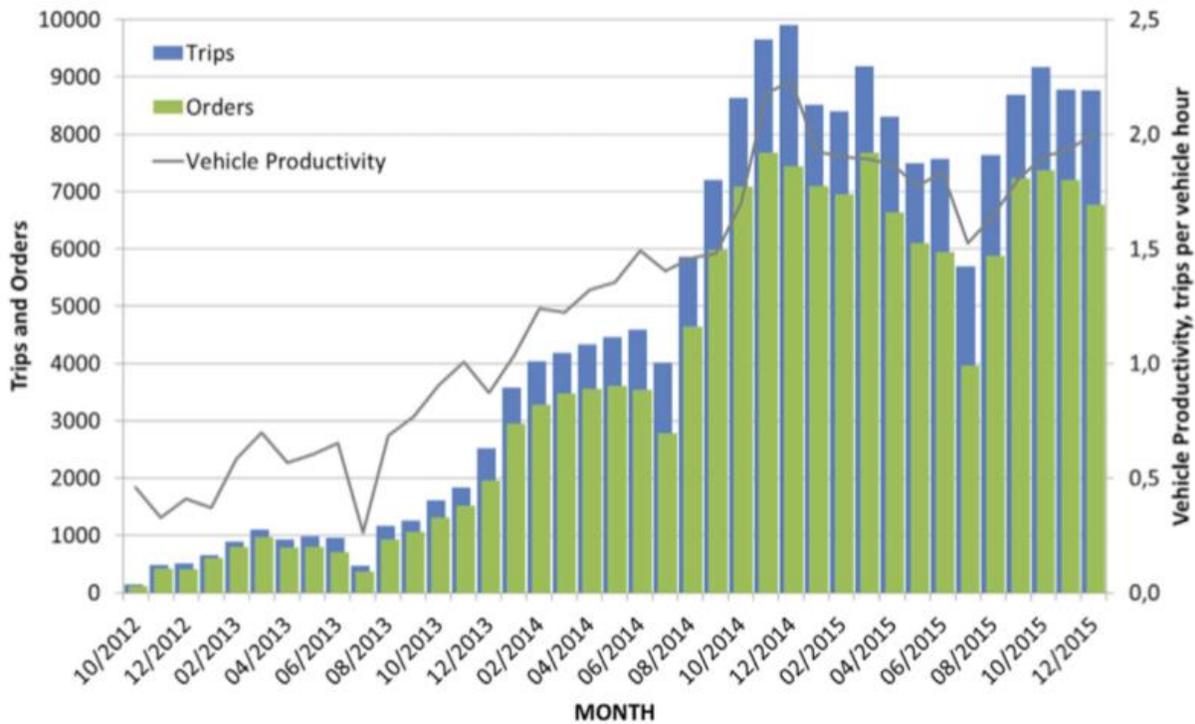


Figure 4.9. Kutsuplus trips and vehicle productivity over project lifetime (source: Haglund et al., 2019).

In the past five years, entrepreneurial technology companies have ventured into the provision of microtransit service with mixed results. Chariot operated flex route service with “crowd-sourced” stops in several US cities beginning in 2014 (Marshall, 2019) and was acquired by Ford. After struggling with low ridership and driver training issues, Chariot eventually ceased all operations in 2019. Bridj, another microtransit start-up, partnered with the Kansas City transportation authority to provide commuter shuttle-oriented demand response service branded as RideKC: Bridj. The service failed to make an impact on the transit environment. Most residents in the service areas were not aware of the service, and the majority of those who were aware of it chose not to use it because it did not serve the areas they needed (Shaheen et al., 2016b). Ultimately the \$1.5 million program shut down after providing just 1480 trips, and Bridj shut down US operations shortly thereafter (Marshall, 2017).

Of all the microtransit start-ups, Via seems poised to make the most of future opportunities. Initially launching in New York City in 2013, the company had over 60 deployments worldwide by 2019 (Mobility, 2019). Initially focused on their own app connecting drivers and riders onto shared rides as a for-profit company, they still operate service independently and without government subsidy in New York, Chicago, and Washington, DC.

Much of the company's expansion has come from Via's partnerships with governments and transit agencies. After years of being the largest North American city without public transport, the Dallas suburban community of Arlington launched its own municipal buses in 2013 (Barry, 2013). Just five years later, Arlington substituted this nascent fixed-route system for a partnership with Via, providing demand-response trips within the city center and to a regional rail station for a flat fee of \$3 (see **Figure 1.1(a)**). Branded as "Arlington-on-Demand", Via's agreement with the city provides a base fleet of 13 vehicles (increased to 15 in 2019), but Via also contracts with independent TNC drivers to enter the fleet at times of high demand. In this way, the capacity provided can flex to meet the demand, decreasing the cost of operation. Pickups and drop-offs are unrestricted within the service areas, but the single most popular pick-up/drop-off point is the regional rail station - which is an exclave of the service area. Not counting auxiliary vehicles, the service averages about 3.1 pickups per vehicle hour on weekdays for an overall farebox recovery of 30%. Arlington-on-Demand continues to expand, and other cities like Los Angeles and Seattle are signing on for similar service (Korosec, 2019b; Grossman, 2019).

To analyze the quality and efficiency of Via services compared with ride-hailing services and fixed-route bus lines, Boston Consulting Group and BCG Henderson Institute (Hazan et al., 2019) studied Via services in four locations: Arlington (Texas), Berlin, Seattle, and West Sacramento (California). All these services are operated by Via under contracts with public authorities and local transport agencies to provide a public transportation solution that did not exist (Arlington), to fill in gaps in the existing mass-transit infrastructure map (Berlin and West Sacramento), or to offer first- and last-mile coverage to nearby stations and stops (Seattle). The four case studies demonstrate that in the right regulatory context, such on-demand mobility

initiatives can benefit passengers and cities alike with lower per-passenger subsidies than those provided to comparable public services.

Per Hazan et al. (2019), findings showed that the average number of passengers carried by each van in an hour ranged from 3.6 to 4.3 compared to an average utilization of 1.9 by similar DRS in the US (such as those offered in suburban and rural areas). With a cost per ride of \$8 to \$11, Via's service (in Arlington and West Sacramento) is far less expensive than the US national average of \$38 for traditional DRS. The percentage of capital and operating expenses covered by fares (i.e., fare recovery ratio) in West Sacramento is 2.5 times greater than the national average for similar DRS systems; this is also higher than that the ratio for the fixed urban bus systems in the US. A reduction of 36% of total vehicle miles traveled in Arlington suggests that on-demand transit could help cities reduce traffic by 15% to 30%. With a larger fleet, on-demand transit could probably have a significant impact on emissions reduction; Via services in the West Sacramento and Arlington save an estimated 60 and 150 tons of CO₂ emissions annually. Hazan et al. (2019) recommend creating a regulatory framework with a mix of positive and negative incentives to encourage transit ridership.

While better known for its private ride services, Uber has been involved in a number of microtransit pilots. While many cities will partner with Uber or other TNCs to provide free or subsidized trips around town, only a few locales have designed these offerings for shared rides (Woodman, 2016). In 2017 the Canadian town of Innisfil, Ontario partnered with Uber to provide shared trips in lieu of a fixed-route bus (Bliss, 2019). All trips within city limits are discounted by \$5, and trips to certain regional attractors are charged a flat \$3-\$5 fare. The program has been popular with citizens, and in 2019 the municipal subsidy for the program has grown \$900,000. In order to curtail costs, Innisfil raised fares and introduced monthly caps on the number of trips each user can take. Elsewhere, Uber has released Express POOL service which aims to be a more streamlined version of their pooled rides by requiring riders to walk to a common meeting point (Nickelsburg, 2018). Globally, they also have operated bus service in Cairo, Egypt and Monterrey, Mexico - showing their ambition to be involved across every segment of the transportation market (Thorne, 2019).

4.4. Design lessons

In 2018 alone at least 24 agencies debuted microtransit pilots, but this considerable interest still begs the question of what role do these services play and how they meet the mission of transit agencies (Lazo, 2018). In most transit agencies, the worst performing fixed route bus lines bottom out at around 10 passenger trips per vehicle hour (Walker, 2018b). Meanwhile, the best purely demand-response systems at best achieve 4 pickups per hour. Those which exceed that level to reach up to 7 or 8 do so by basing the service on a flex route pattern or anchoring one end of the service at a transit hub.

Despite lower productivity rates, transit agencies could still value microtransit for several reasons. First and foremost, it can be a way to extend service coverage to an area at a lower cost. This coverage goal is often motivated by reasons of jurisdictional equity - providing some access to service to communities that contribute to the transit tax base who otherwise would not receive fixed-route service. For example, AC Transit in Alameda County, CA, eliminated a low-performing bus route and replaced it with a microtransit service. In a blog post describing the experience, AC Transit planner John Urgo argued that the use of smaller buses provided enough savings to cover the added cost of the software (Urigo, 2018). This lower vehicle operating cost can also be seen in **Figure 4.10** plotting the productivity of RTD's fixed routes and demand response services from Volinski (2019). Comparing the purple "Call-n-Ride" marks to the blue fixed-route marks at the lower end of the spectrum, switching service to demand response reduced the cost per boarding significantly.

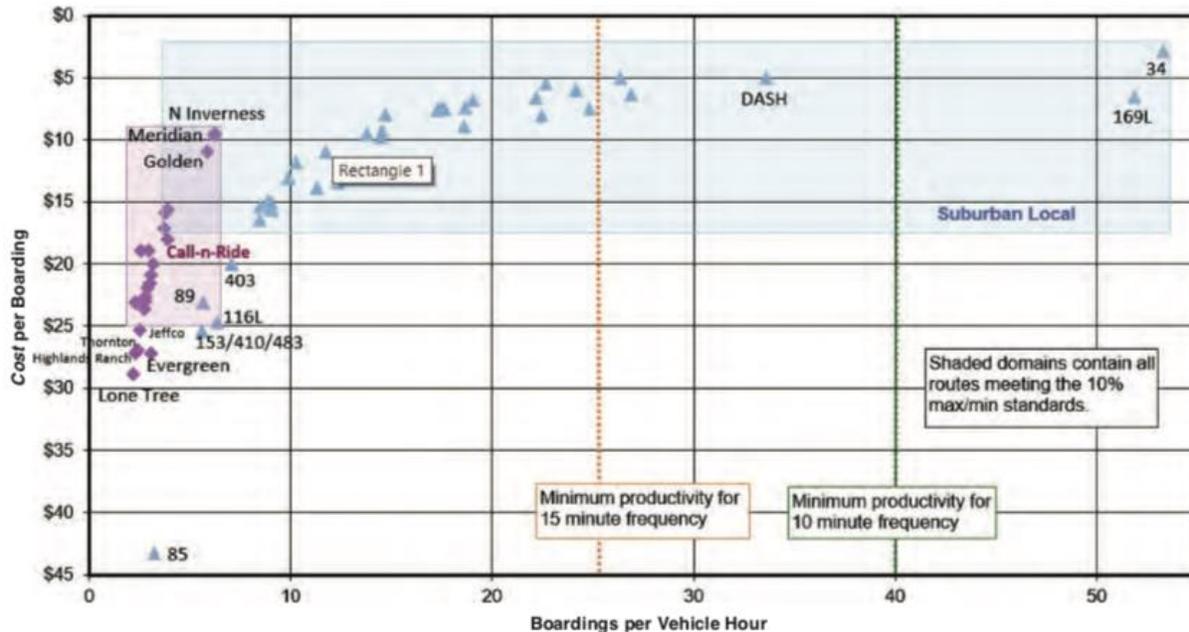


Figure 4.10. Denver RTD Cost per boarding versus Boardings per Vehicle hour. Fixed routes in blue triangles and demand-response service in purple diamonds (source: Volinski, 2019).

The Cherrlots West Salem Connector is an instructive case study in these dynamics. Designed to replace a low-ridership fixed route bus line, the West Salem Connector FMLM service area was designed to increase service coverage in a revenue neutral way. The Connector was reasonably successful, averaging 3.3 passenger pickups per vehicle hour (Volinski, 2019). One of the main issues was frequent long wait times, indicating a demand for service that outstripped the available capacity. However, adding another vehicle to the Connector would have raised the costs of the service beyond that of a fixed route. Therefore, in 2017 the transit agency redesigned the service area to include a new fixed route, using demand data from the Connector service as part of the planning process.

As this example shows, once a microtransit service reaches a certain level of productivity, it's likely better served as a fixed route. Granted, if the curb-to-curb nature of demand response service is of importance to the target population, then the "breakeven" productivity level may be higher. Therefore, it's likely that the specific users of the system who benefit from demand-

response microtransit are different than those who benefit from equivalent fixed-route coverage. Furthermore, this breakeven point is dependent on differences in hourly operating costs between fixed-route and demand-response. The cheaper demand response service is, the more likely an agency will be able to serve an arbitrary service area at an average cost competitive to fixed-route service. If there's no difference in hourly operating costs, agencies are likely better off operating a more productive fixed-route equivalent. Generally, the more a system is structured towards fixed route, the more productive it will be.

Finally, one must consider the user inputs to the service. Fixed route service is more productive because passengers spend their own time and energy to gather at a bus stop, allowing the bus to follow a more direct route and make fewer stops overall. These user costs can be particularly onerous in the use cases for microtransit, often chosen for locales where the land use patterns make fixed route service expensive and for customers that are less mobile. Thus, microtransit is best suited to geographic regions where fixed-route transit would face difficulty from high access costs (hilly terrain, poor pedestrian infrastructure, circuitous street networks, etc.). Schaller (2018) suggests these services to best operate as extensions as opposed to replacements for fixed route.

The interaction between shared on-demand mobility services and high-capacity public transit plays an important role. In recent years, the International Transport Forum (ITF) at the Organization for Economic Co-operation and Development (OECD) has conducted several simulation studies to investigate the impact that the shared on-demand mobility services would have on replacing other forms of transport such as traffic congestion, air pollution etc. Using the existing network data and application of real mobility services within an actual urban context, different reform scenarios have been analyzed in these studies. This includes shared mobility simulations for Auckland, New Zealand (OECD/ITF, 2017a); for Lisbon, a European city (OECD/ITF, 2015; OECD/ITF, 2016; OECD/ITF 2017b); and for Helsinki, Finland (OECD/ITF, 2017c). These studies analyzed the complete or partial replacement of private car traffic with shared on-demand mobility.

As we move towards a future that will bring the autonomous vehicles and shared mobility together, a recent case study by the Oslo Region public transport company (Ruter, 2019) investigates the consequences of a fully automated fleet and digitalized transportation while elaborating on the possibilities of autonomous vehicles facilitating MaaS services in the Oslo region (Scandinavia). The study considers different scenarios in the future where autonomous vehicles and MaaS-based car sharing schemes replace private car ownership; the scenarios capture the extremities where all cars are fully automated. Six different scenarios are modeled in the study; four main scenarios and two sub scenarios that are variations of the main scenarios (summarized in **Figure 4.11**).

In the most optimistic scenario, the traffic volume (i.e. vehicle kilometers driven) can be reduced by 14% (i.e, in scenario 1b where all car users share their rides, and PT users continue using PT). As the study operates with a high service level for the MaaS system, this implies short waiting times and no long detours. For longer detours, traffic volumes may be reduced by up to 31 % in scenario 1b. Overall, findings show that with ridesharing and a high share of public transport riders, the MaaS system can help to achieve the climate change adaption target in the Oslo region.

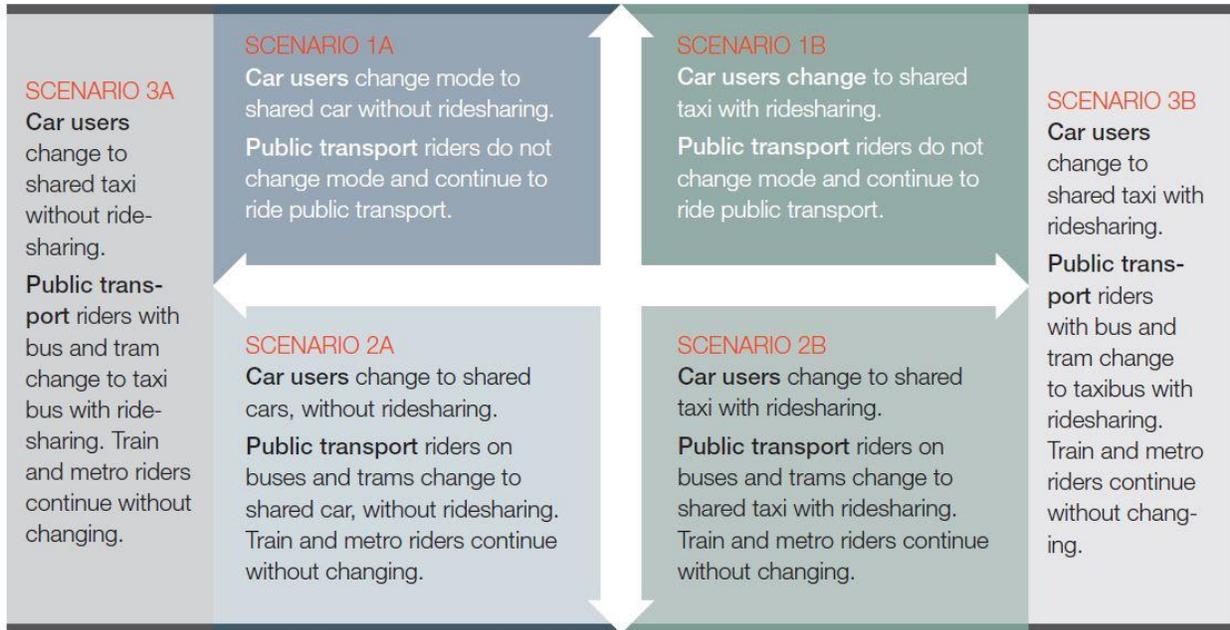


Figure 4.11. The six scenarios in the Oslo study (source: Ruter, 2019).

Section 5: Technological and Institutional Challenges

While flexible transit services have plenty of potential in providing efficient and viable transport service in urban, suburban, and rural areas, the successful implementation of such services requires overcoming a range of barriers. Velaga et al. (2012) identify major challenges like technological, financial, integration, shortage of vehicles, safety, reliability, demand uncertainty, and performance evaluation measures faced by existing flexible transport services (in rural areas). Mulley et al. (2012) explore the extent to which a variety of barriers have been encountered and tackled in the USA and Europe. The authors categorize barriers into institutional frameworks (such as policy and regulation), issues (funding and fares), operational issues (fleet and vehicles), operator and community, and information and education.

The following sections provide an overview of key challenges confronted in the development of flexible transit services, based on existing studies that address these issues and discuss solutions/steps to overcome the same. We categorize the major challenges as technology, infrastructure, market dynamics, and governance.

5.1. Technology

The difficulty in predicting varying travel demand in low-demand areas and the lack of efficient real-time communication systems between transit service providers and customers pose a challenge in providing flexible transit services. Wilson et al. (2009) explore the current and potential future use of automated data collection systems (ADCS) for the public transport agency functions. Examples include service and operations planning, service control and management, customer information, and performance measurement. The authors classify ADCS systems into automatic vehicle location and tracking systems (AVLT), automated fare collection systems (AFC) and automated passenger counting systems (APC). Specific applications of ADCS are discussed, including estimation of passenger origin-destination matrices (for system usage) and the estimation of path choice models for (passenger behavior), using Chicago transit authority rail network data. For any proposed transit operating plan, quantifying such behavioral decision rules can be used to forecast the change in the spatial distribution of passenger flow required for efficient public transport planning.

Many of the innovations in microtransit operations came with the introduction of Global Positioning system (GPS) that tracks the vehicle in real time. Brake et al. (2007) summarize the

main architectural components of telematics based flexible transit service as the control center (known as travel dispatch center: TDC), devices for customers to access the service, and communication network (Brake et al., 2007). It is crucial to ensure that potential users of such flexible services remain informed of the services available/accessible to them.

Since the 1990s, technologies (labeled broadly under the umbrella of “intelligent transportation systems” (ITS)) have been standardized within a national ITS Architecture (see Harvey et al., 2016). With the widespread adoption of ridesharing services, the National ITS Architecture was updated with such a service package TI06 shown in Figure 5.1.

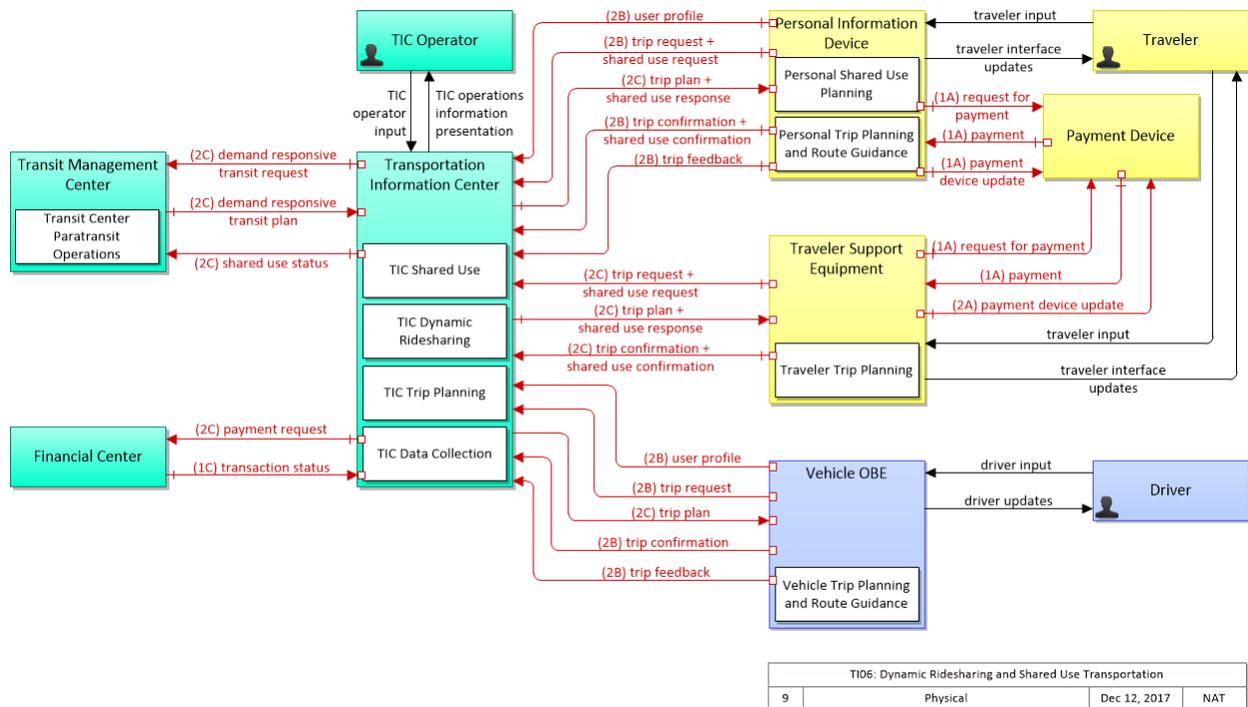


Figure 5.1. Dynamic ridesharing and shared use transportation service package (source: ARC-IT, 2020).

The availability of large-scale trajectory data obtained from mobile phones has also been a transformative development for public transit planning. Pinelli et al. (2016) apply this data source to the public transportation network planning problem, designing transit routes solely from observed mobility demand patterns. They demonstrate their model on mobile data from Abidjan, Côte d’Ivoire, and find a 27% reduction in user travel times if the proposed transit routes are used instead. Williams et al. (2015) use cell phone data to formalize routes for bus services operated in Nairobi, Kenya, shown in **Figure 5.2**.

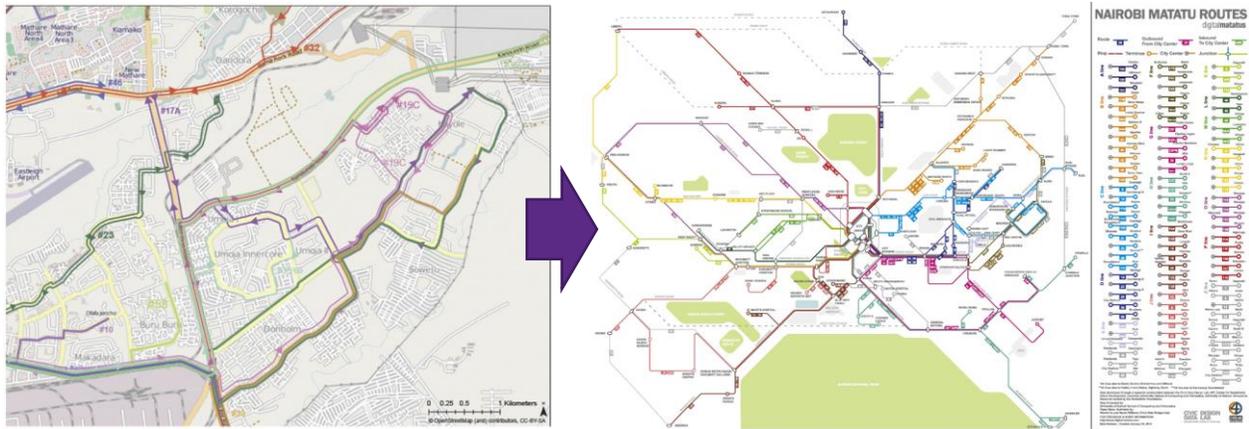


Figure 5.2. Use of cell phone data (mapped on left) to construct routes and timetables for Nairobi, Kenya (source: Williams et al., 2015).

The fact that the provision of real-time information makes it more convenient for commuters to use transit services is supported by many studies (Taylor and Fink, 1996; Abdel-Aty and Abdel-Aty, 2001; Tang and Thakuriah, 2011; Peng et al., 2002; Zhang et al., 2008). Tam and Lam (2005) study the market penetration of personal public transportation information system (PTIS). Using a binary logit model (from a stated preference survey) to investigate how passenger demographics and trip characteristics would affect the market penetration of the personal PTIS, the study finds that the number of transfers required for completing a journey, departure time, travel time, income, and mobile telephone ownership are significantly related to the demand of the personal PTIS. Service charge and length of delay in receiving information would negatively affect the demand for the personal PTIS.

Using survey data on users' views on real-time bus information systems, Rahman et al. (2013) estimate the threshold value of transit headway below which real-time information is no longer perceived as important. The authors suggest the implementation of real-time bus information on bus routes where the bus headway is longer than 10 minutes. The study also examines the error margins that people are willing to accept from real-time information system (e.g., early/late bus arrivals than estimated arrival times). However, respondents are quite sensitive to an increase in fare for the sake of obtaining such information. Watkins et al. (2011) study users' perception of a higher wait time without real-time bus information system (relative to actual wait time). A critical finding of this study is that the actual experienced wait time is

reduced when mobile real-time information is available (riders with real-time information wait almost 2 minutes less than those arriving using traditional information).

In some cases, institutional factors may drive the technological solution adopted in transit systems, e.g. smart cards for fare collection (e.g., use of smart cards may facilitate distribution of funds between local authorities and transit operators). In the United States, smart card implementations can be found in New York, Washington, Chicago, and San Francisco, and in more than 10 other metropolitan areas. Pelletier et al. (2011) discuss several uses of data collected by smart cards in the context of strategic (long-term planning), tactical (service adjustments and network development), and operational (ridership statistics and performance indicators) levels in public transit management. Moreover, the authors also address storage issues, privacy concerns and legal issues related to the dissemination of smart card data. The study identifies potential challenges for smart card transit operators which includes further investigation on technological improvements, data validation, economic feasibility, journey validation, destination estimation, network performance, and new modeling approaches.

In addition to users' data, the systems data (such as AVTL) can be used for improving flexible transit service performance. General Transit Feed Specification (GTFS) (and the GTFS-realtime extension) is a data specification that allows public transit agencies to publish their system data in a standardized format to be used by a variety of software applications. For example, OneBusAway, a suite of transit traveler information tools, provides real-time arrival information, a trip planner, a schedule and route browser, and a transit-friendly destination finder for Seattle area bus riders (Ferris et al., 2009). Williams et al. (2015) describe how GTFS can be adapted to semi-formal systems and be used by other cities (with similar transit systems) for planning, research, operations, and transit routing applications. However, the major challenge lies in integrating the systems data (general transit feed specification) and user data for flexible transit systems planning (by researchers and transportation planners). To address this challenge, Lorion et al. (2014) present guidelines to include models for data-driven flexible transit services, technologies to integrate and visualize data, and methodologies to evaluate the demand for such services at a societal level in transit systems planning education.

With MaaS, cities are looking to a similar standardization for data sharing as ITS saw with ITS architecture in the 1990s. For example, the Los Angeles DOT created a Mobility Data Specification (MDS) (Zipper, 2019) to make it more seamless for operators like micromobility providers to work with transit authorities. An obstacle to adoption of such specifications is the privacy concern. One way to overcome this is to design data privacy control mechanisms, with

several examples emerging from the literature (Aïvodji et al., 2016; Hallgren et al., 2017; He et al., 2017a; Chow, 2018; He et al., 2018; He and Chow, 2019).

Another important direction for technology innovation is having computational effective algorithms to handle path selection and generation for multimodal networks. Due to their nature with incomplete/uncertain information (e.g. common lines, Chriqui and Robillard, 1975), heterogeneous preferences in multimodal routes (Liu et al., 2010; Arentze and Molin, 2013), and dynamic operational setting (Wilson and Nuzzolo, 2013), selecting routes is not trivial. One example is Delling et al. (2015), who developed new algorithms to compute all Pareto optimal journeys in a dynamic public transit network that includes arrival times and transfers. These developments have led to new tools like the open-source Open Trip Planner, which has been adopted by several agencies as shown in **Figure 5.3**.

OpenTripPlanner Deployments Worldwide

Official Production

The following are known deployments of OTP in a government- or agency-sponsored production capacity:

- **Finland (nationwide)** The [Helsinki Regional Transport Authority](#), the [Finnish Transport Agency](#), and other [Finnish cities](#) have collaborated to create [Digitransit](#), providing OTP-based trip planners, APIs, open data, Docker containers and open source code. Each member organisation runs its own instance of a shared codebase and deployment environment. Their source code is available [on Github](#), including a [new custom UI](#). This system also has a strong real-time component.
- **Norway (nationwide)** Ruter provides a [journey planner for the Oslo region](#). It has been in production since January 2016 and serves around 200,000 users per day. Since November 2017, Entur has also provided a [nation-wide journey planner](#) which consumes schedule data in the EU standard NeTEx format with SIRI realtime updates.
- **Portland, Oregon** TriMet is the agency that originally started the OpenTripPlanner project. Their [Regional Trip Planner](#) is based on OTP and provides about 40,000 trip plans on a typical weekday.
- **New York State** The State Department of Transportation's [transit trip planner](#) provides itineraries for public transit systems throughout the state in a single unified OTP instance.
- **Los Angeles, California** The new [metro.net trip planner](#).
- **Atlanta, Georgia** The Metropolitan Atlanta Rapid Transit Authority's (MARTA) [trip planner](#) and the Atlanta region's transit information hub [attransit.org](#) both use OTP to power their website trip planners.
- **Boston, Massachusetts** The [Massachusetts Bay Transportation Authority trip planner](#).
- **Seattle, Washington** The [Sound Transit Trip Planner](#) is based on OTP. OTP also powers the trip planning feature of the [OneBusAway native apps](#) in the Puget Sound region. Technical details are [here](#).
- **Tampa, Florida** Hillsborough Area Regional Transit uses an OpenTripPlanner server to power the trip planning feature of the [OneBusAway native apps](#) in their region. Technical details are [here](#).
- **Piemonte Region, Italy** and the [City of Torino](#) built on OpenTripPlanner by [5T](#).
- **Valencia, Spain** from the Municipal Transport Company of Valencia S.A.U.
- **Grenoble, France** from SMTC, Grenoble Alpes métropole, l'État Français, the Rhône-alpes region, the Isère council and the City of Grenoble.
- **Rennes, France** where the STAR network provides an OTP client for [iOS](#), [Android](#), Windows Phone et Web.
- **Alençon, France** integrated urban and school bus network [planner from Réunion Alençon](#).
- **Poznań, Poland** from Urban Transport Authority of Poznań (ZTM Poznan).
- **Trento Province, Italy** - [ViaggiaTrento](#) and [ViaggiaRovereto](#) were implemented as part of the [SmartCampus Project](#), a research project founded by [TrentoRise](#), [UNITN](#), and [FBK](#).
- **University of South Florida** (Tampa, Florida). The [USF Maps App](#) is a responsive web application for that helps university students, staff, and visitors find their way around the campus using multiple modes of transportation, including the USF Bull Runner campus shuttle, Share-A-Bull bike share, and pedestrian pathways. Open-sourced [on Github](#).

Figure 5.3. Open Trip Planner deployments (OTP, 2020).

There are also new tools to evaluate new transit operations and technologies for planning and policymaking. Traditionally, planning tools like Emme³, TransCAD⁴, and Cube⁵ provide network analysis tools to evaluate different transit network designs. Open source alternatives exist as well (e.g. AequilibraE). However, static assignment models do not capture dynamic interactions between user activity schedules and service schedules. Tools like FAST-TrIPs⁶ address this with dynamic passenger assignment. However, they do not consider alternative service operations like microtransit or MOD. At the other extreme are the simpler sketch planning tools like the web-based interface offered by Remix⁷, which is helpful for policymakers to look at data collaboratively and assess alternatives at a high level.

For more in-depth analysis of the impacts of transit (and MaaS) network alternatives on travelers in a city, some researchers have turned to multiagent simulations. One such tool is MATSim⁸, which is an open-source simulation platform that simulates a population of travelers. The tool considers a day-to-day adjustment process (see Djavadian and Chow, 2017a,b) driven by heuristics to evaluate market equilibrium for the system serving a synthetic population to their daily schedules. Becker et al. (2020) used the tool to evaluate the impact of having carsharing, bike-sharing, and ride-hailing all in the presence of public transit in Zurich. An illustration of the interactions that can be analyzed is shown in **Figure 5.4**.

One example of the use of MATSim for public transit evaluation is in NYC, where C2SMART researchers have developed a proprietary NYC-MATSim simulation consisting of over 8 million synthesized population for the year 2016 that includes all the major modes of transport in their agendas. A visualization of the calibrated network (for a 4% scaled population) is shown in **Figure 5.5**. Using this simulation, the team can evaluate the Brooklyn Bus Network Redesign proposed by the NYU Marron Institute (Goldwyn and Levy, 2018) and output the forecasted ridership at each proposed stop in the network shown in **Figure 5.6**. The analysis is discussed in greater detail in a forthcoming publication⁹.

³ <https://www.inrosoftware.com/en/products/emme/>

⁴ <https://www.caliper.com/tcovu.htm>

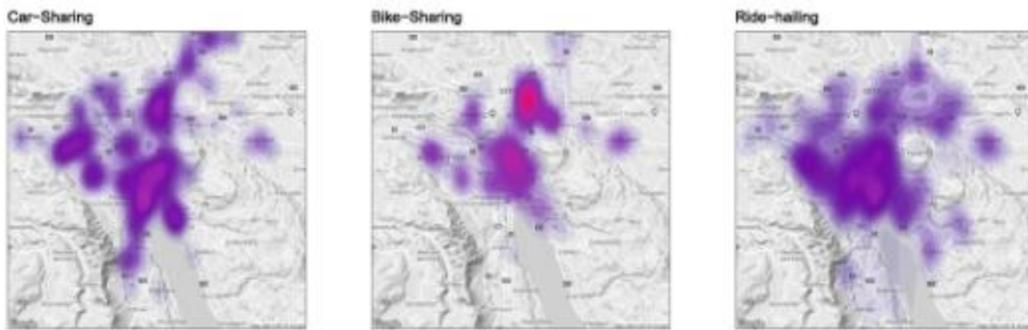
⁵ <https://www.citilabs.com/software/cube/>

⁶ <https://github.com/Fast-Trips>

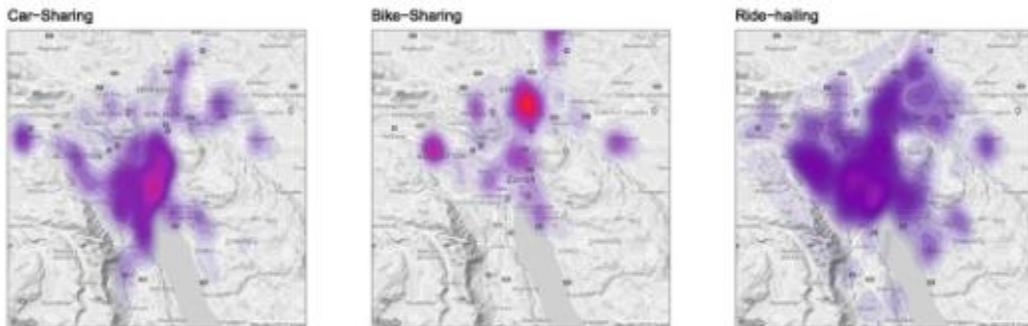
⁷ <https://www.remix.com/>

⁸ <https://www.matsim.org/>

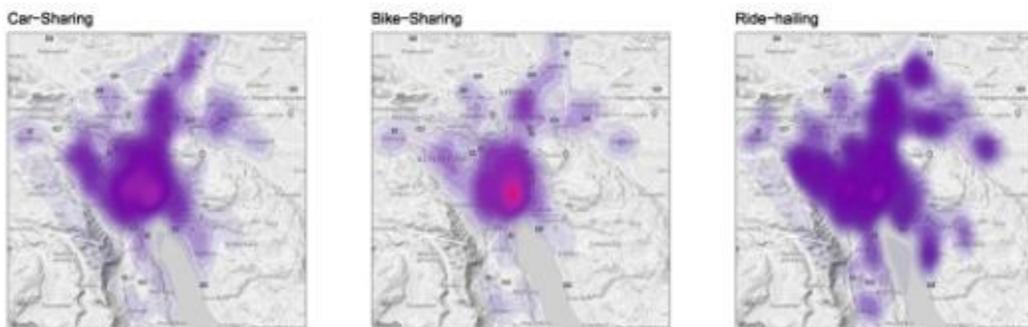
⁹ <http://c2smart.engineering.nyu.edu/2019/05/24/simulation-analytical-evaluation-bus-redesign-alternatives/>



(a) Only one service operating in the area. Fleet size is 250 in each case.



(b) Each service simultaneously operating with fleet size 250.



(c) Each service simultaneously operating with fleet size 4000 for car- and bike-sharing and 1000 for ride-hail.

Figure 5.4. Rental start locations under (a) solo service; (b) all services simultaneous with 250 fleet size; (c) all services simultaneous with 4000 car- and bikeshare and 1000 ride-hail (source: Becker et al., 2020).

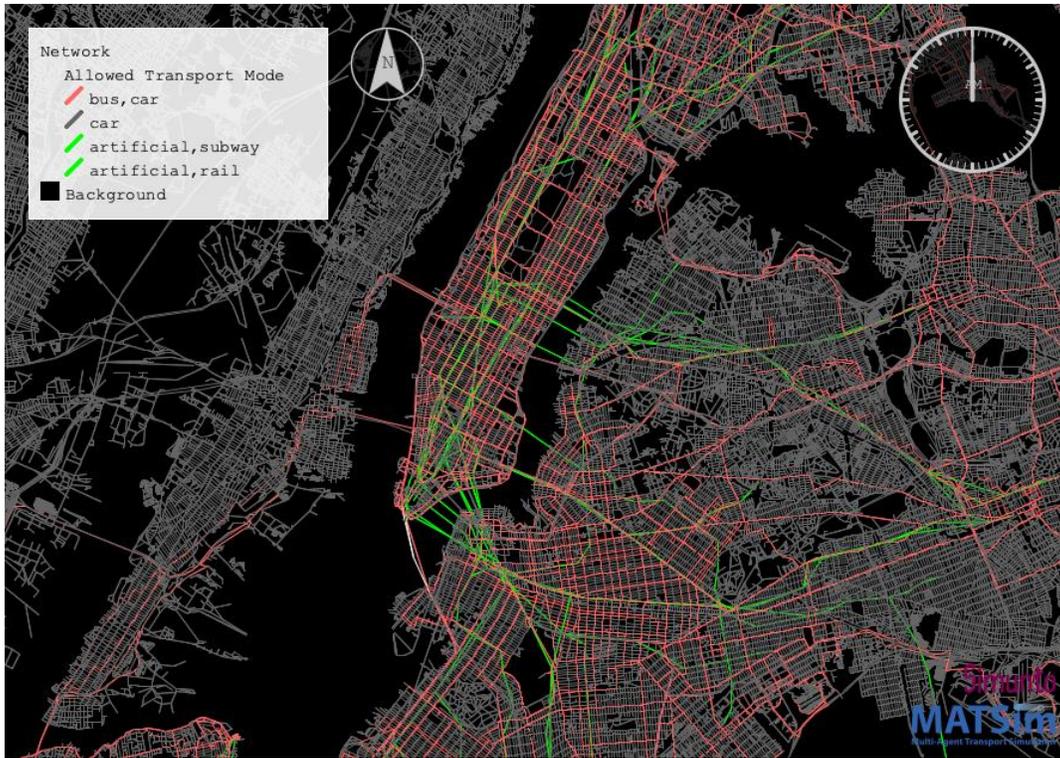


Figure 5.5. NYC-MATSim created by C2SMART researchers.

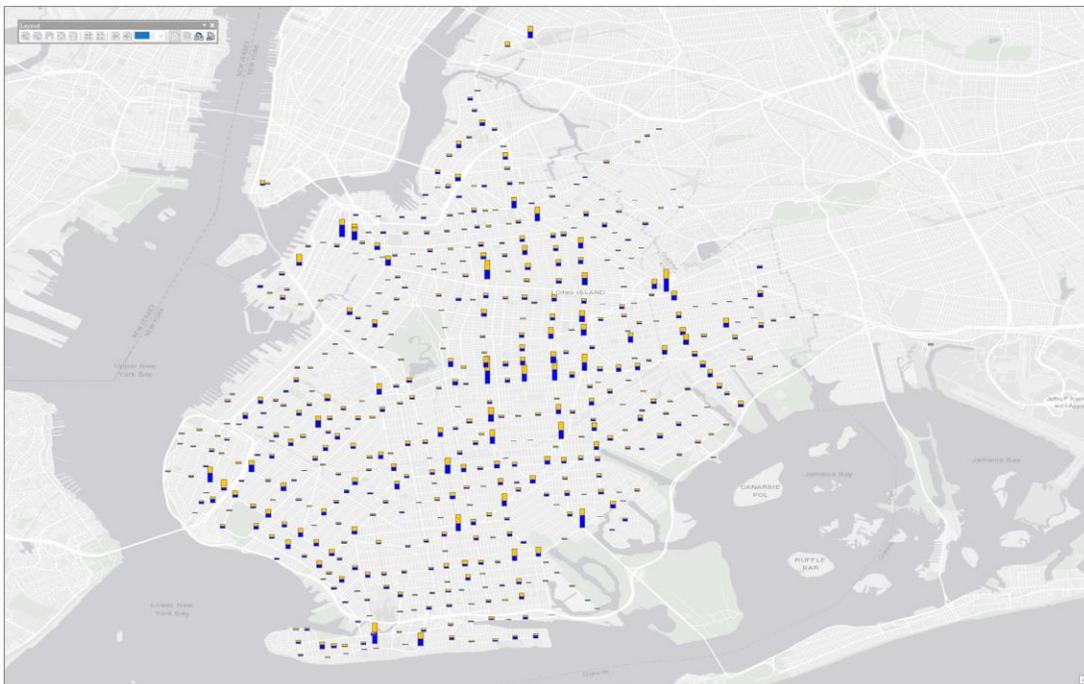


Figure 5.6. Forecasted boardings and alightings in proposed bus network redesign from Marron Institute using NYC-MATSim.

5.2. Infrastructure

The way a transit service operates and interacts in the urban environment, is largely achieved by planning the transit capacity and its quality of service. The TCRP Report 65 (Ryus et al., 2013) provides a transit manual with guidelines and tools for transit capacity and quality of service (TCQSM) evaluation. This includes quantitative techniques for calculating the capacity and other operational characteristics of bus, rail, demand-responsive, and ferry transit services, as well as sizing elements of transit stops, stations, and terminals.

Bus speeds can be improved by operating bus lanes below their capacity (thereby minimizing interference between buses), and by facilitating skip-stop operations. An optimization method for designing limited-stop services was proposed by Leiva et al. (2010). The objective of the study was to determine the lines and frequencies to be offered by such services such that it minimizes the social costs of a segregated bus lane. The total cost includes variable operating costs (including employment costs, bus acquisitions, taxes, licenses, and insurance) and user costs (categorized as access time cost, wait time cost, in-vehicle cost, and transfer time cost). The model assumes known trip demand and accommodates transferring between bus lines and vehicle capacity constraints. The savings obtained by offering limited-stop services were found to be significant; higher benefits were observed for greater demand variability and longer trip lengths.

Besides skipping stops or providing limited stops, another approach to improving the typical bus-only lanes is by providing an additional signal upstream of the main signal (called a *pre-signal*). Güler et al. (2014) suggest that such a pre-signal can be used to better use the capacity of the main signal while still providing bus priority to reduce the system wide person hours of delays. The motive behind this study is the potential reduction of total discharge flows caused by an underutilized bus lane running through a bottleneck. These reduced discharge flows can increase car delays.

In a similar context, He et al. (2017b) consider strategies that share road space capacity in a flexible manner at a given element of the arterial. These strategies use flexible space allocation for buses to move in front of the car queues without continuously banning cars from using one full lane. The authors propose an analytical framework for quantitative evaluation of bi modal systems to examine flexible sharing strategies. In a bimodal system, different modes can

discharge using separate capacities or with a total capacity (these capacities also depend on the mix of the modes). Two principles guide how to efficiently install these strategies along a given arterial (at some critical bottlenecks) and provide requirements for such strategies.

In designing a suitable and cost-effective flexible transit system in any environment, the decision on the type of vehicle to be used plays an important role. Wright (2013) show that the product of demand multiplied by the average trip distance provides a strong indicator for the vehicle type to be used. Based on this, service design guidance (on appropriate vehicle selection) is proposed for new services or for improving poorly performing services. A population density-adjusted threshold for subsidy per passenger trip is considered as an indicator for the service performance. The trade-offs are shown in **Figure 5.7**.

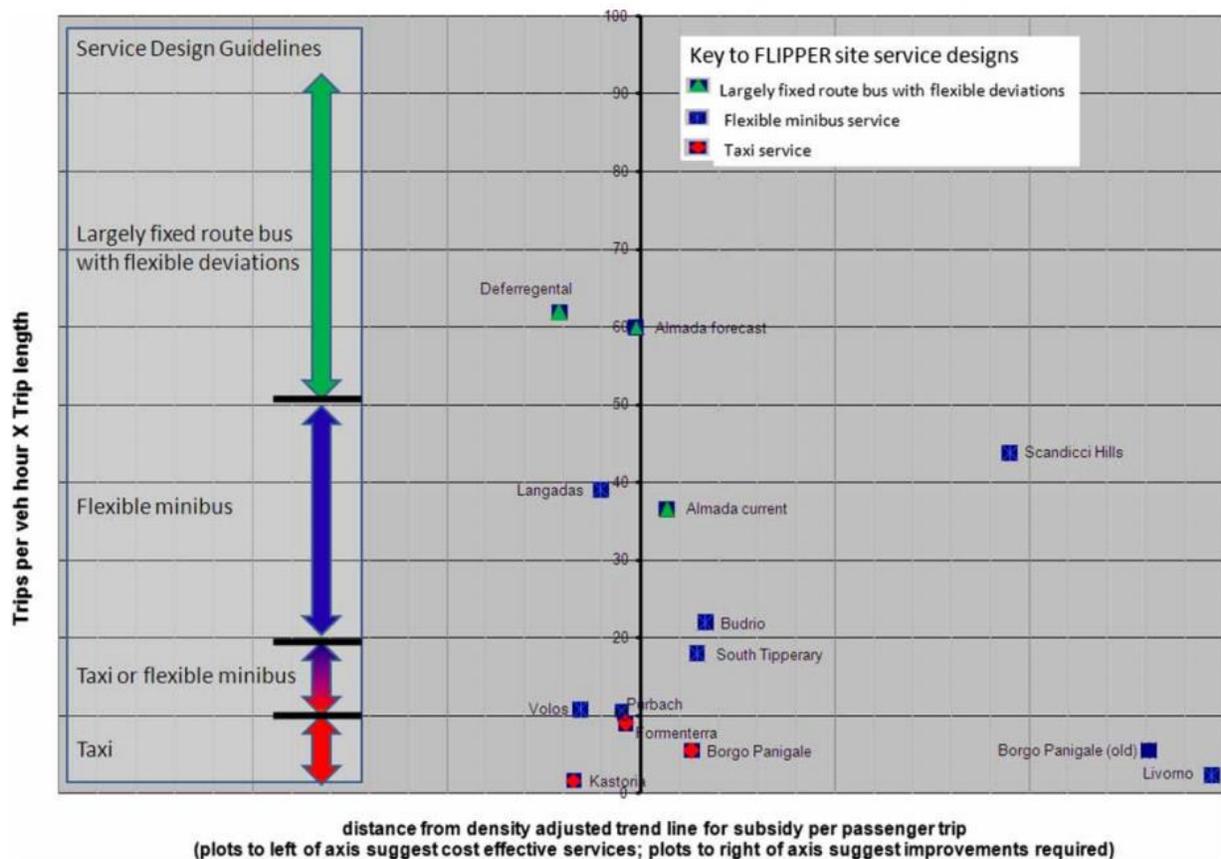


Figure 5.7. Service design guidelines vs “trips per vehicle hour × trip length” (source: Wright, 2013).

To encourage people to take public transport for part of their trips, park-and-ride facilities (P&R) have been identified as a viable travel demand management strategy. Wang et al. (2004)

studied an optimal location and pricing of P&R facility considering a linear city where residential population is uniformly distributed from the Central Business District (CBD) out to the (fixed) city boundary. Deterministic mode-choice equilibria are solved before and after the introduction of P&R under profit maximization and social cost minimization objectives. A “win–win” situation exists whereby such a facility can be profitable and socially beneficial at the same time. This can help a transit operating agency determine when, and how, a P&R service can be established that meets profitability and/or social welfare improvement goals.

The load capacity of a transport system does not only refer to spatial facilities (such as road links) but also includes non-spatial queueing facilities such as parking structures or transit station platforms. Chow and Djavadian (2015) consider activity scheduling patterns of travelers (from an aggregate perspective) and propose a market equilibrium model for multimodal transport systems to capture both the activity behavior and the capacity effects of the system. This model can evaluate trade-offs between parking demand and capacity with respect to mode choices in an activity-scheduling context.

5.3. Market dynamics

Transit ridership is largely a function of price and service characteristics (i.e., quality of service) experienced by the passengers. Research works on evaluation of fare changes of transit system mostly assess fare options using economic efficiency criteria (such as revenue changes and ridership). However, social equity, and economic considerations may be considered for evaluation. In view of this, Cervero et al. (1990) highlight various fare policies and practices. Although the response to fare structures or payment methods vary among user groups and operating environment, it is found that some riders are twice as sensitive to changes in travel time as they are to changes in fare. Moreover, people are more sensitive to service improvements than to the fare discounts. Cross elasticity research suggests ridership improvement can be better achieved by higher automobile prices than by lower fares.

Shen et al. (2017) propose a service-based fare strategy to assist transit planners in designing appropriate fare structure when current fixed-route transit turns to flex-route policy. This fare structure is based on the variation of service quality as well as cost of provision after implementing the flex-route operating policy. Given that the service vehicle visits all

checkpoints and the curb-to-curb requests make the reservation during the day before, the proposed fare structure includes the following three levels:

- Two-deviation group (type 1 passengers: starting point and destination not at checkpoints),
- One deviation group (type 2 passengers: starting point at checkpoints, and destination not at checkpoints; type 3 passengers: starting point not at checkpoints, and destination at checkpoints), and
- Regular passenger group (type 4 passengers: starting point and destination both at checkpoints).

The service quality function is constructed as the sum of expected walking time, expected waiting time, and expected riding time. The authors assume the default slack time per cycle to be equal to the actual running time without deviations (in order to accommodate more requests: high demand) and the riders are equally sensitive to changes in service quality and in fare levels.

Rasulkhani and Chow (2019) study the competition between different operators on a common platform. The platform may be interpreted from a traditional sense as the built environment managed by a public agency; it can also be interpreted more explicitly as a digital platform (like Moovel or Global MaaS) managing services from multiple operators. The competition can be modeled as a cooperative game between operators and travelers illustrated in **Figure 5.8**. The model essentially takes potential routes and user demand to output: lines operated, passengers served, and costs (fares and other cost transfers between users and operators, e.g. locations of (virtual) stops that impact access time) such that no operator or traveler would break their coalition. The methodology has been implemented to evaluate kussbus, a microtransit service operating out of Luxembourg (Ma et al., 2019).

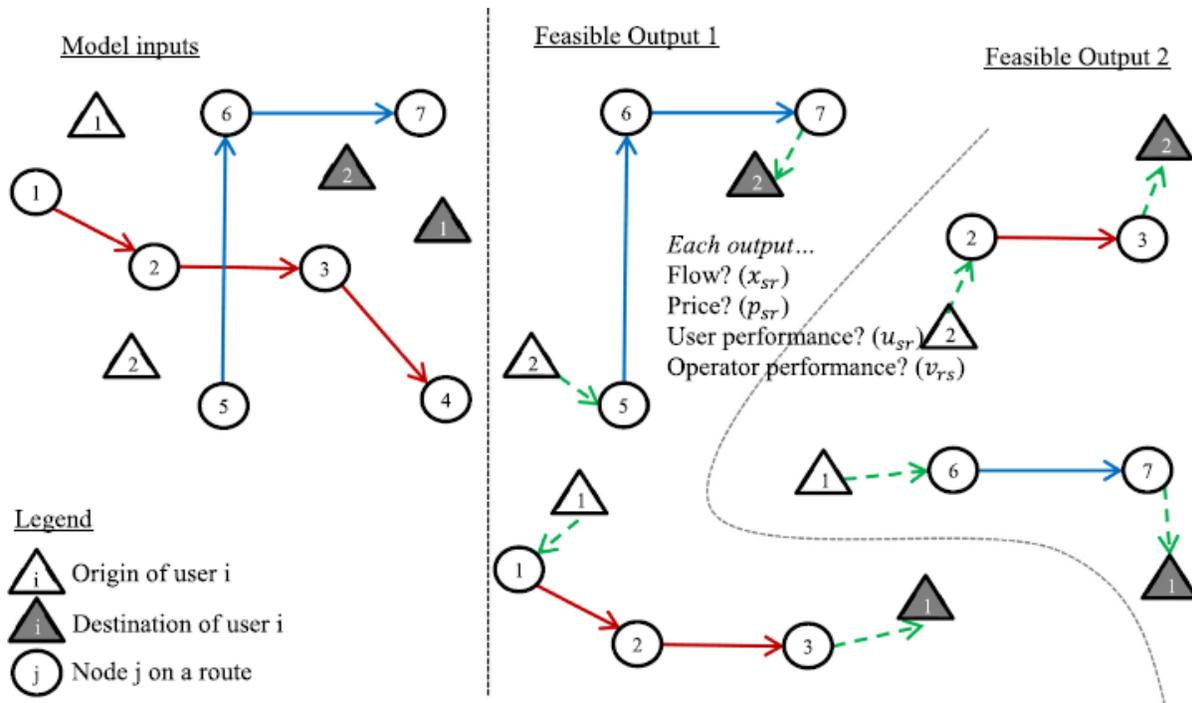


Figure 5.8. Illustration of different assignments using the model (source: Rasulkhani and Chow, 2019).

This model can benefit different user groups; it can help operators to design ticket pricing, routes/schedules that impact access/egress, quantify the impacts of fleet operational algorithms in terms of user incentives (such as those requesting passengers to meet at pickup locations to reduce routing costs), whereas policy makers can use this to decide shared policies that impact wait/transfer costs, analyze infrastructure policies that impact those operators (such as congestion pricing or allocated parking spaces for shared mobility services).

Pantelidis et al. (2019) generalizes the approach to allow for coalitions formed by multiple operators to serve passengers on multimodal trips. Using this model, a platform or agency facilitating a market of operators can evaluate a broader range of scenarios that include new firm entry, government acquisition of an operator, effects of capacity increases, or technological improvements (e.g. routing algorithm advances) that lead to reductions in traveler or operator costs. As the MaaS projects collect more data, this model can be used to fit to that data to help design the platform to be stable.

Masoud et al. (2017) introduce a concept of P2P ride exchange to reverse the negative impacts of the first come first serve (FCFS) rule on system performance, without increasing the complexity of the problem. An attempt to reverse the impact of the FCFS rule is done by proposing to a rider (who has been offered an itinerary) to switch to a less attractive itinerary, thereby liberating the drivers (providing service to the rider's current itinerary) from their commitments. A monetary compensation from a second rider (who finds the liberated drivers more valuable) motivates this exchange. The P2P exchange mechanism proposes the amount of this compensation with an objective to increase ridership while ensuring that the system balances the budget. The designed mechanism is limited to bilateral trades (where there is a single buyer and a single seller) and is optimal for a one-to-one matching system. Findings from the study suggest that this mechanism results in higher performance levels and customer retention rates (than the standard FCFS allocation) and provides a lower-bound on the increase in ridership in one-to-many and many-to-many systems.

In an automated, dynamic ride-sharing system, drivers and riders do not necessarily have to accept match proposals by the ride-share provider. Therefore, to consider the stability of the proposed ride-share matches, Wang et al. (2017) propose a stable matching game where no rider/driver (in a one-to-one system) can be better off by unilaterally switching to other drivers/riders. The authors used several mathematical programming methods to establish stable or nearly stable matches, at the cost of only a small degradation in system-wide performance (in terms of system vehicle miles savings). The study defines transient stability as stability with respect only to information known at a time 't', and posteriori stability as stability given the complete set of trip announcements that are received during an operating day. The proposed approach can lead to more sustainable ride-sharing systems in the long run. However, for it to yield operationally efficient results, the mechanism requires access to the participants' trip information in advance.

The concept of combining transportation services from public and private transportation providers through a unified gateway to create and manage a trip, i.e. MaaS, has been studied quite extensively in recent years. The impacts of MaaS on future public transport contracts in the new digital age are addressed by Hensher (2017). The study presents a number of positions that could potentially represent future contexts in which bus services might be offered, recognizing that a hybrid multi-modal state of affairs (point-to-point MaaS) may be the most appealing new contract setting, enabling the design of contracts to be driven by the mode-neutral customer experience.

To evaluate the market equilibrium for MaaS systems considering users' travel behavior and operators' incentives, Djavadian and Chow (2017a) explore flexible transport services in the framework of two-sided markets. The authors extend an earlier day-to-day adjustment process (Djavadian et al., 2017b) to include day-to-day adjustment of the service operator(s) as the seller and the built environment as the platform of a two-sided market. The comparison between a one-sided market and two-sided market demonstrates their differences and shows how to identify thresholds for when network externalities lead to two-sided markets. The study also demonstrates the sensitivity of the day-to-day model to operating policies. The agent-based stochastic user equilibrium obtained with the proposed adjustment process (using Ramsey pricing criterion) show that a perfectly matched state from a day-to-day process is equivalent to a social optimum.

A novel perspective on line planning in public transportation is presented by Schiewe et al. (2019). Line planning aims at determining the routes (called lines) which are served regularly by a vehicle and the frequencies of these services. The authors in the study interpret line planning as a routing game where the passengers are players who choose routes by minimizing individual objective functions composed of travel time, transfer penalties, and a share of the overall cost of the solution. The study investigates under which conditions a passenger's best-response can be calculated efficiently (using a best-response algorithm to find equilibria) and which properties are needed to guarantee convergence of the best-response algorithm.

5.4. Institutional barriers and governance

Because of their hybrid approach to the provision of mobility, flexible transportation systems are often viewed as a "special" service requiring an independent funding source. This can often lead to the premature demise of a system after that single funding source is eliminated (Mulley et al., 2012). Flexible transportation systems are inherently less productive than fixed-route systems, and they rely disproportionately on government funding streams even more so than fixed route service. Distance-based subsidy agreements further complicate this funding vulnerability. If operators are compensated on a per-mile basis, funding for flexible transit is inherently less predictable because the mileage covered is variable. Further exacerbating the financial strain is that flexible transit may be more expensive per mile operated in some cases.

For most US agencies flexible transport means ADA paratransit. As a provision of the Americans with Disabilities Act, public transportation agencies that operate fixed route service must offer complementary ADA paratransit available everywhere within three-quarters of a mile of each fixed-route line. While some agencies cover their entire operating region to simplify operations and system legibility, in many environments the minimum requirements create “paratransit deserts” - large areas where paratransit is unavailable in an otherwise contiguous metro area. The imposition of ADA requirements upon transit agencies has important internal consequences. Because the mandate is unfunded and paratransit trips are always more costly to provide, flexible-route services are viewed as a resource drain on the prime directive of providing fixed-route service (Mulley et al., 2012). At the same time however, ADA requirements can spur innovation in flexible transportation services. Koffman (2004) notes that a small agency in Virginia decided to provide flex-route bus service instead of fixed-route partly in order to avoid the ADA paratransit requirement associated with fixed-route transit. Thus, the US legal environment has both driven the proliferation of flexible transportation and relegated it to second-class status in the eyes of many.

If an agency is interested in implementing flexible transportation, the specifics of the labor agreements can significantly impact the ease and costs of doing so. Volinski (2019) reports that most agencies contract flexible transportation services out to their paratransit provider for greater flexibility and system familiarity. Where paratransit service is provided “in-house,” agencies may rely on the specifics of the bargaining agreement in order to feasibly provide a new pilot service.

With emerging mobility services dominating the landscape, the institutional challenges have shifted somewhat. In the US, MaaS is often described as individual mobility services such as car sharing and ride sharing. With the continuous rise of such services, automated taxi service is anticipated to be the single major mode of transport in the long run. Enoch (2015) envisages a model that converges buses, taxis, and cars due to a desire for point-to-point services, a desire for lower cost, and due to externalities respectively into a universal automated taxi system, shown in **Figure 5.9**.

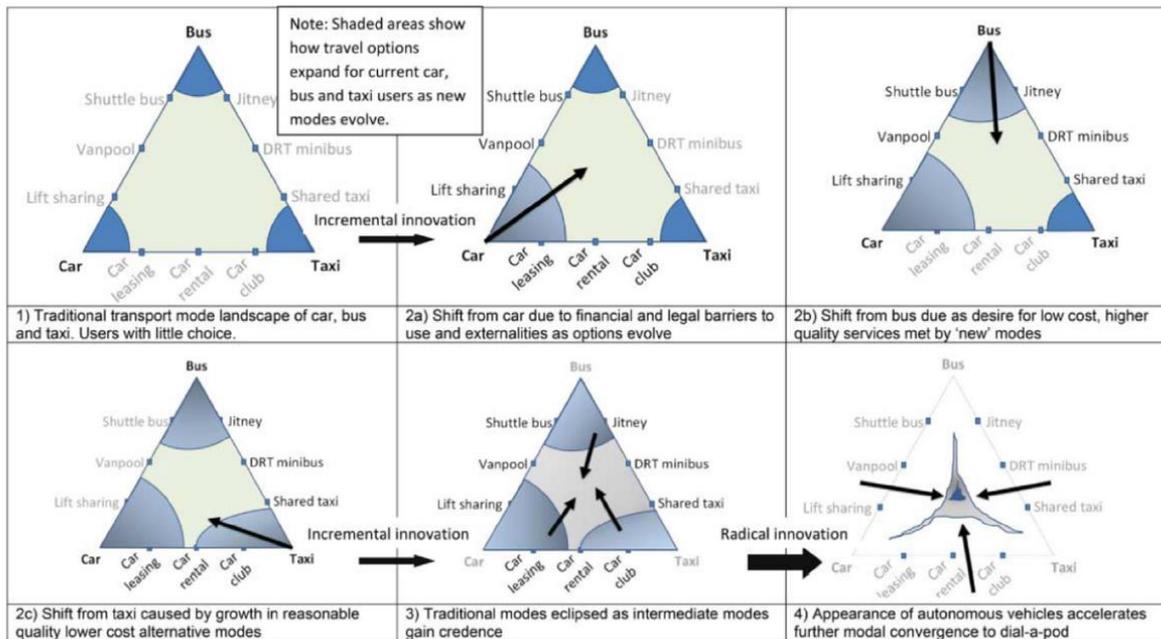


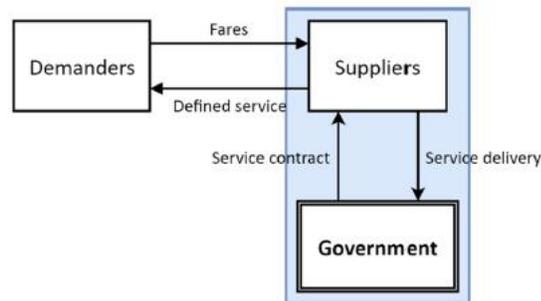
Figure 5.9. Urban passenger modes converging towards an automated taxi service (source: Enoch, 2015).

Wong et al. (2019) address the problematic outcomes of modal displacement and/or modal convergence by proposing a framework to integrate all involved actors, including individual modal operators and their regulator(s). The framework aims at improving the broader transport system by linking urban land use characteristics to travel price and modal efficiency to guide the sustainable development of our cities. The study defines the efficacy of various transport modes with reference to their spatial efficiency (passengers per vehicle/train consist or per unit road space equivalent) and temporal efficiency (proportion of time a vehicle spends on the road in revenue service for public transport) to serve as a criterion for transport policy. The modal efficiency framework in **Figure 1.2** situates public, private, active and shared modes with respect to their spatial and temporal efficiencies. The center of mass for modal displacement and modal convergence scenarios resides in the *shared modes* quadrant (bottom right).

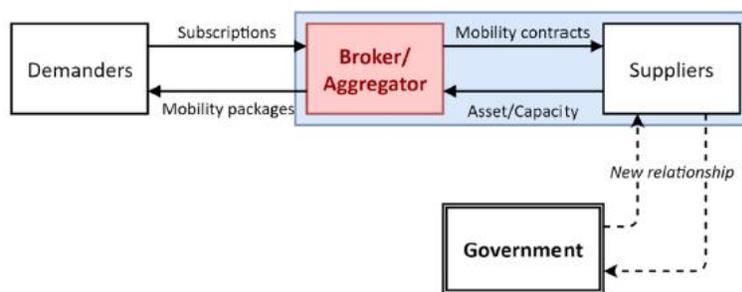
In this new paradigm of spatial and temporal integration, MaaS is considered an enabler of an efficient transport network and whose potential role must be operationalized by a service delivery model to bring together a range of actors. The status quo in terms of how traditional public transport has been delivered includes the government (regulator) contracting the suppliers (operators) to deliver public transport services for demanders (customers). This

traditional paradigm is represented as Model A (**Figure 5.10**) by the authors. A new business entity i.e., the MaaS broker/aggregator is introduced in Model B and C in **Figure 5.10**. Mobility brokers purchase the transport asset/capacity from various suppliers including those providing investment, expertise and service and integrate them as mobility plans or packages for demanders to subscribe.

A: Conventional public transport under status quo



B: Mobility as a service under economic deregulation



C: Mobility as a service under government contracting

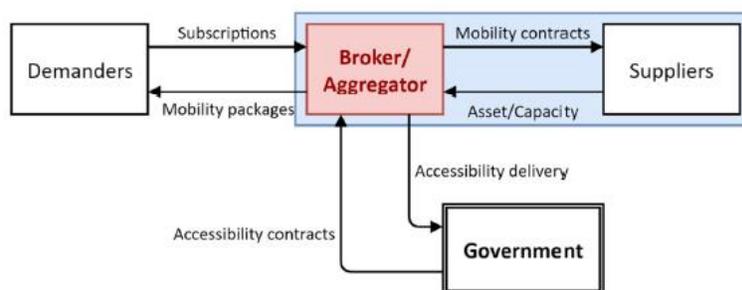


Figure 5.10. The present service delivery model for conventional public transport (Model A) and proposed frameworks for MaaS under economic deregulation (Model B) or government-contracted scenario (Model C) (source: Wong et al. 2019).

In Model B, the government can only influence MaaS operators at the margins, specifying the conditions and barriers for market entry. It is otherwise a market-driven scenario including any impacts on modal shift, congestion, data sharing/exchange and the economy. In this setting, the commercial imperative motivating MaaS actors may or may not align with government objectives for transport and land use. This may entail risks such as monopolistic and predatory behavior from larger brokers or suppliers; there may be a financially driven impetus to substitute customers away from public transport towards less spatially efficient modes.

In order to avoid unintended consequences, Model C considers moving from self-regulation towards government acting as an independent regulator (similar to the Office of Rail and Road (ORR) and the Water Services Regulation Authority (Ofwat) in the United Kingdom). The service delivery model (Model C) proposed is a government-contracted model that shifts public transport contracts from their present output-based approach, delivering kilometers traveled, to outcome-based models delivering accessibility.

In this model, the government directly procures a mobility broker through a competitive tender, and once the market has matured, there is opportunity to negotiate contract renewal at subsequent rounds. The accessibility standards are set by the government that may be defined as delivering X percentage of people services within Y minutes, for a given period (using any mode of the broker's choosing). The broker can operate or subcontract ride hailing and microtransit in the suburbs, and the point-to-point service can be priced at such a premium that restricts demand overflow. Cross-subsidization is encouraged in this paradigm to maintain the full range of service offerings across spatially efficient modes and for transport equity considerations. To meet any funding gap, there exists the prospect of financial support from government in this approach. One of the most promising opportunities under a contracted MaaS ecosystem is the ability for government to regulate for network efficiency by incorporating a road user charge as an input into the package price.

However, various unanticipated consequences such as wellbeing, emissions, and social inclusion could arise from any widespread roll-out of MaaS. Pangbourne et al. (2019) suggest potential governance and policy-making responses to the challenges of urban governance for the packaged services MaaS model. To mitigate against undesired implications and achieve benefits, there is a rationale for government intervention on efficiency (public goods, addressing externalities and conditions of market failure) and equity (such as social inclusion, intergenerational equity and spatial justice). MaaS should not be more expensive than the

current transport system and should be fully inclusive. While MaaS promises efficiency to cities, freedom to citizens, and profit to service providers, such promises do not guarantee efficiency or equity. Hence public authorities need to be involved in piloting and implementation of MaaS trials. The removal of barriers to implementation to private commercial organizations to facilitate MaaS services could reduce opportunities to develop open-source standards on the functional requirements for MaaS operation. This gives the private sector the power to control inter-organizational learning while hiding key details of evaluations behind commercial confidentiality. Revisable data sharing schemes would help protect the citizens using the applications right from the beginning of MaaS planning periods.

Pangbourne et al. (2019) recommend that MaaS requires more envisioning rather than forecasting to develop future strategies. The governance actors can explore the consequences of decisions (as per the distributed social and environmental needs of the jurisdiction) about which modes to prioritize; this will enable them to specify MaaS packages that could be both efficient and equitable. This may be used for joint planning of the built environment and the mobility system (beyond data and service integration). Public interventions would be possible by engaging citizens (through (non)-digital technologies) in continuous envisioning processes, including social simulation, permitting the public to set parameters for simulation runs, and discussing the effects.

Information barriers associated with flexible transportation are often among the most critical and difficult challenges to overcome. The means with which people normally encounter fixed route transit are not as potent for flexible transportation. Traditional fixed-route buses are large, easily identifiable to an agency, persistently run along the busiest corridors in a region, and, even when the vehicles are not present, their stops are visible. Flexible service, by contrast, operates smaller vehicles that may blend in more with the general traffic mix, run variable routes, and may not utilize any fixed infrastructure at all (Luiu et al., 2018). This renders the service systematically less visible compared to fixed-route options. While most fixed-route lines have been integrated into popular trip planning software, flexible service requires a more complex data standard and remains under-represented. While the development has lagged, a protocol known as GTFS Flex is in development to be compatible with Open Trip Planner and other tools (Sorensen et al. 2019).

Because users are unlikely to encounter flexible transportation options in their normal routines, marketing is a crucial part of orchestrating a successful pilot. For example, Shaheen et al. (2016) determined that not nearly enough marketing had taken place in advance of the Bridj

system rollout in Kansas City, leaving overall awareness of the system remarkably low. In Ireland, where flexible services are less commonly known than in the US, the national Department of Transport's demand response system for rural areas has found success by placing local community leaders as volunteer board members - thus directly planting system familiarity and buy-in to existing community networks (Mulley et al., 2012).

This community buy-in is particularly important for flexible transportation because of the education required for users to understand the service. A lack of understanding of how a flexible service works can impact its usage. Some studies indicate that flexible transportation services can develop demographic-specific stigmas. Glasgow and Blakely (2000) find that some older populations disfavor these services because of the notion that they are for disabled or disadvantaged riders. Some in rural Ireland view flexible transportation as a more feminine mode (Ahern et al., 2012).

We need to examine to what extent these difficulties are endemic to the modal form as opposed to symptomatic of specific organizational and environmental factors. One common theme across traditional and insurgent providers is the importance of education. When Uber launched its UberPool shared ride option, many riders expressed angst when they unknowingly booked a shared option and a stranger suddenly joined their trip (Koebler, 2016). Uber has since added a more substantial indication and micro-orientation to pooled rides in the app. Adding to rider (and driver) confusion is the fact that the fare discount of UberPool is not tied to whether another rider *actually* joins the trip. Henao (2019) has suggested that this discontinuity represents an opportunity for some behavioral user education, tying the ride discount to actualized ride sharing instead of simply the type of request.

Across the other challenges, new companies perform quite well. While their system model is more akin to shared taxi than to flex route bus, shared trip options are seamlessly displayed within app with wait time and arrival time estimates. These shared options are also integrated within trip planners like Google Maps. Via conducts a significant amount of its business not as a transportation provider but as a software service, leasing the use of its routing and scheduling platform to agencies wishing to run their own vehicles and operations (Via, 2018).

In addition to solving the information barrier, TNCs perform quite well against the cultural misunderstanding suffered by some flexible transportation systems. Uber's user base is quite young and disproportionately high income (Kooti et al., 2017), and one would expect that the UberPool demographics be cut from the same cloth (but likely at a lower average income).

Therefore, it seems older people aren't inherently predisposed to using shared, flexible services as some stigmas might suggest.

On the contrary, much has been made of younger generations' proclivity for the sharing economy and lack of enthusiasm towards private car ownership (Birdsall, 2014). Economically speaking, when TNCs partner with local governments to provide subsidized transportation, their arrangements are nearly always a fixed percentage of each trip (Woodman, 2016; Bliss, 2019). This arrangement is far more predictable than the per mile arrangements of many public flexible systems. Furthermore, TNCs' labor costs can be much lower because drivers are independent contractors. This tilts the scales heavily in favor of the operator and opens additional system flexibility. For example, in Via's partnership with the city of Arlington, TX, additional TNC drivers can be pulled into the fleet at peak hours. This fleet flexibility allows them to satisfy peak demand without committing to an oversupply of service during the off-peak. However, this apparent advantage may also open the companies to long-term legal risk. While their independent contractor status prevents TNC drivers from collectively bargaining, some legal scholars argue that it means TNC platforms amount to price-fixing on a massive scale (Gordon, 2019).

This comparison does not imply failures of action for either type of provider. Uber, Lyft, Via, and the rest of the TNCs can make decisions swiftly and unilaterally in a manner that would be anathema to the mission of transit agencies that provide public flexible transportation service. Rather, this comparison is an illustration of what is possible. The rapid adoption of shared rides within app-based marketplaces reinforces the potential of mobility as a service to bring other transportation modes into a similar, shared marketplace.

Section 6: Use Case Study of State-of-the-Art Policies

To make the methods surveyed in this compendium more accessible to readers, a case study is created to demonstrate their usage. Three general classes of transit service design methods are implemented on a common data set:

1. Fixed route service: In this policy, the transit vehicle offers a continuous service along a fixed route moving back and forth between the first and the last stop.
2. Flexible route service: This policy allows deviation of the transit vehicle operating along a well-defined path to serve demand-responsive requests within a zone around the path.
3. Door-to-door service: This is the most flexible transit policy where door to door passenger on-demand requests are served by the transit vehicle.

A synthetic data set is created based on real data from NYC. A common simulation is used to run all three designs to illustrate how they compare. **Given the dependency of these operations on different costs, we are not using this comparison to suggest one service operates better than another since we do not take costs into account.** For example, fixed route buses would have greater passenger capacity than on-demand buses and cost more to operate but run less miles and require less drivers. Instead, the case study is used only to illustrate how a simulation tool can be used to evaluate different operating policies. It is up to the reader to determine the cost requirements for their operations to conduct the comparison.

The case study provides readers with a tool for them to adjust their own values to output results for comparison. Section 6.5 discusses how a practitioner can adapt the simulation tool to other lines around the world to evaluate these methods in designing services elsewhere.

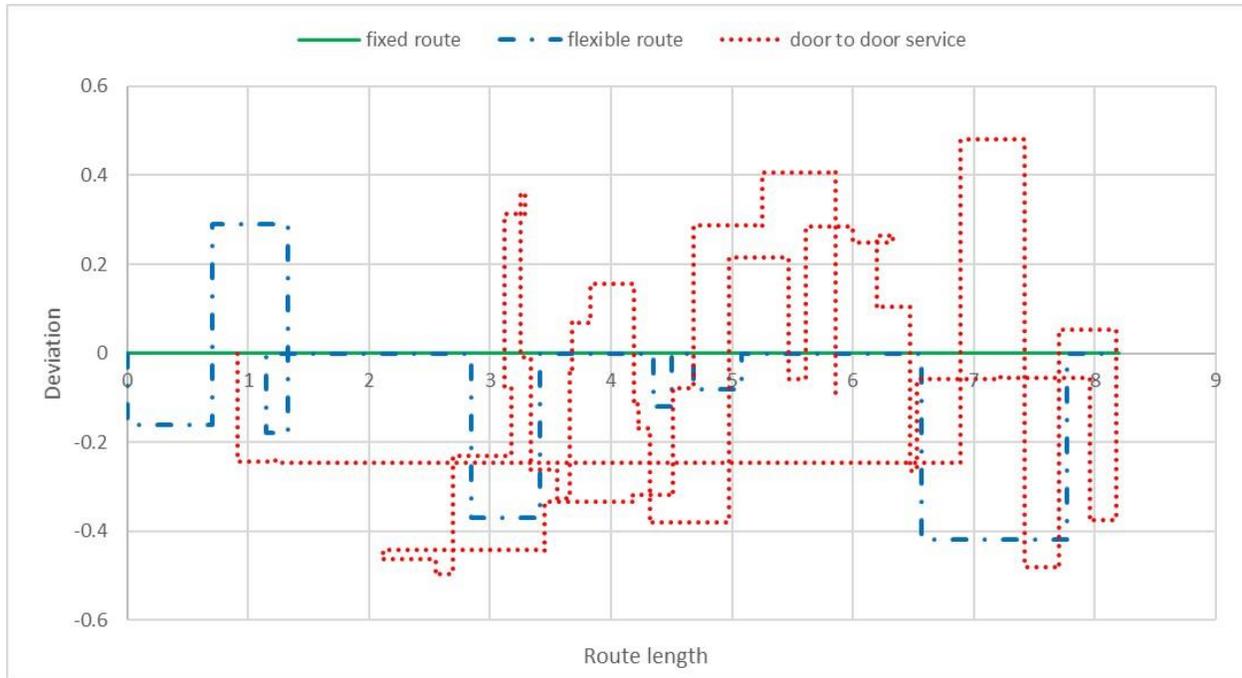
6.1. Simulation

The simulation tool is designed to run one of three different operating policies for a rectangular service region around an existing or potential bus line of width W and length L . Any existing line can be converted into this equivalent rectangular space. An example is shown in **Figure 6.1** for the B63 line in Brooklyn, NY. **Figure 6.1(a)** illustrates the trajectory of 5-checkpoint flexible route service and an on-demand service trajectory overlaid on a 57-stop

fixed route service in GIS. **Figure 6.1(b)** illustrates how those locations are treated within the simulation setting as part of an equivalent rectangular space.



(a)



(b)

Figure 6.1. (a) Illustration of three vehicle trajectories based on fixed route, flexible route, and door-to-door service overlaid on the B63 line in Brooklyn; (b) the same trajectories converted to a rectangular space for running the simulation.

The simulation is event-based; it simulates the vehicles in a fleet as agents according to their operating policy and the origin departures, boarding, alighting, and destination arrivals of a set of passenger agents over a time period. The OD locations and arrival schedules of passengers can be input to the simulation so that either observed data or pre-simulated arrivals can be used and be identical for all three operating policies. The simulation also outputs the same performance measures.

Simulation inputs:

- Line length L (miles)
- Service area width W (miles)
- Time period T (sec)

- Time step τ (sec)
- Dwell time t_d (sec)
- Vehicle running speed v_o (mph)
- Walk speed v_w (mph)
- Walk limit ζ_a (mi)
- Passenger set is $W = \{O, D, \Omega\}$, where O is the set of origin locations (x-y coordinates in rectangular space), D is the set of destination locations (x-y coordinates in rectangular space), and Ω is the set of origin departure times (sec) of the passengers
- Fleet size V
- Vehicle capacity K

The simulation outputs the following variables and performance measures.

Simulation outputs:

- Set of passenger boarding, alighting, and destination arrival times and locations; acceptance/rejection status; expected and realized access/egress/wait/in-vehicle times; assigned vehicle; pickup/drop-off locations
- Set of vehicle trajectories per second; vehicle loads; served passengers; segment travel times; vehicle idle time
- Aggregate performance measures: average wait time; average in-vehicle time; average access/egress time; total vehicle mileage; perceived journey time; maximum vehicle load; ridership

Since the policies differ, the simulation logic also differs for each case. This is described as follows.

6.1.1. Fixed route simulation

A fleet of buses travel from one terminal to the next according to a specific headway, visiting each stop along the way.

1. Define system settings (route configuration, vehicle specification), including the following inputs:
 - Headway h (sec)
 - Number of stops S (which is evenly distributed along route by default, but locations can be specified)
2. Warm up to locate vehicles along the route.
3. Initiate passenger requests as they arrive (request time, origin, destination).
4. Assign passengers to the bus which arrives next if there is capacity. Otherwise, assign to the next available one.
5. Update assigned passenger boarding time and serving vehicle trajectory and load.
6. Simulate vehicles' trajectories according to the operating policy.
If a vehicle is staying at a stop, calculate remaining dwell time. If it is shorter than a time step, the vehicle starts to move.
If a vehicle is moving along the assigned route, it keeps moving if it does not reach the next stop within a time step. Otherwise, it stops moving.
7. After the simulation ends, aggregate performance measures.

6.1.2. Flexible route service simulation

Each bus in the fleet goes from terminal to terminal stopping at each checkpoint for a length of time. Along the way, any passenger arrivals are checked to see if they are assigned to the bus at which point it would deviate off route to the passenger's location or for the passenger to deviate to the route. Vehicle deviation only occurs if it does not exceed the buffer time allotted at each checkpoint.

1. Define system settings (route configuration, vehicle specification), including the following inputs:
 - Cycle time t_c (sec) – this determines the buffer time at each checkpoint
 - Number of checkpoints S_c (which is evenly distributed along route by default, but locations can be specified)
 - Maximum wait time ζ_w (sec)
 - Maximum backtracking distance ζ_b (mi)
2. Warm up to locate vehicles along the route.
3. Initiate passenger requests as they arrive (request time, origin, destination).
4. Estimate performance change of available vehicles if they accept a new passenger request under operating policy.
 - 1) A vehicle directly serves a passenger from their origin and destination
 - 2) A passenger walks to one of the segments of the existing routes of each vehicle to increase a possibility to be served
5. Evaluate alternatives and choose the vehicle impacted the least regarding total user cost.
 - 1) If there is no vehicle to serve a passenger under an assumed threshold for maintaining service quality, the system refuses to serve the passenger.
 - 2) If a passenger is rejected from the system, they are assumed to walk to the nearest checkpoint and return to Step 3.
6. Update assigned passenger and serving vehicle information.
7. Simulate movements of vehicles according to their status.

If a vehicle is staying at a stop, calculate remained dwell time. If it is shorter than a time step, the vehicle starts to move.

If a vehicle is moving along the assigned route, it keeps moving if it does not reach the next stop within a time step. Otherwise, it begins to stay.
8. After the simulation ends, aggregate performance measures.

6.1.3. Door-to-door service simulation

A fleet of vehicles located at a set of depots and assigned to pick up and drop off passengers as they arrive, door to door or stop to stop.

1. Define system settings (vehicle specification, depot location), including the following inputs:
 - Depot locations S_d
 - Distribution of fleet to depots
 - Maximum detour time per passenger ζ_t (sec)
 - Maximum wait time ζ_w (sec)
2. Initiate passenger requests as they arrive (request time, origin, destination).
3. Estimate performance change of available vehicles if they accept a new passenger request using operating policy.
 - 1) Evaluate alternatives and choose the vehicle impacted the least regarding total user cost.
 - 2) If there is no vehicle which can serve passenger under assumed threshold for maintaining service quality, the system refuses to serve the passenger.
4. Update assigned passenger and serving vehicle information.
5. Simulate movements of vehicles according to their status.

If a vehicle is staying at a stop, calculate remaining dwell time. If it is shorter than a time step, the vehicle starts to move.

If a vehicle is moving along the assigned route, it keeps moving if it does not reach the next stop within a time step. Otherwise, it stops moving.
6. After the simulation ends, aggregate performance measures.

The simulation code was written in MATLAB, a commercial computer programming language providing. MATLAB codes will be available on a GitHub repository¹⁰. “Main.m” is functioning as a control panel of inputs. Users can adjust simulation parameters and choose a system to simulation. As targets of the simulation are three distinctive mobility services, the code has three major parts; fixed route system (“FixedRoute.m”), flexible route system (“FlexibleRoute.m”), and door-to-door service (“DtD.m”). They identify simulation elements, initialize vehicle information, determine passenger-vehicle matches, and produce simulation outputs by organizing other function accordingly.

In **Table 6.1**, the descriptions of common functions are provided. Each system shares common procedures despite some minor differences in detail. Names of functions are extended in the simulation using a “suffix” such as “_Fix”, “_Flex”, or “DtD” to distinguish their parent function.

Table 6.1. Simulation code dictionary

Function	Description
<i>All policies</i>	
“IdentPax.m”	Receive passenger information and prepare arrays for intermediate outputs
“Insert.m”	Conduct insertion heuristic to evaluate candidate routes and archive the best one for each vehicle
“Dwell.m”	Process passenger pickup when staying at stops and determine vehicles’ movement when leaving stops
“VehBrdAlght.m”	Determine vehicles’ movement when moving and process passenger pickup and drop-off when arriving at stops
<i>Flexible route policy</i>	
“PaxApproach.m”	Identify feasible segments for passengers’ approach
“EvalSeg.m”	Evaluate candidate routes considering intersections with approaching passengers and archive the best one for each vehicle
<i>Technical functions that provide simple calculations</i>	
“GridDist.m”	Receive passenger information and prepare arrays for intermediate outputs
“Navigate.m”	Yield the anticipated location after a given time or calculate a required time to reach the next point

¹⁰ https://github.com/BUILTNYU/FTA_TransitSystems

6.2. Operating policies

The simulation is developed to run three different operating policies. They are described in this section. These policies in the simulation can be replaced in the future with other operating policies.

6.2.1. Fixed route policy

The analytical expression for a bus line operation discussed in Section 2.2.2 is used to design the policy consisting of number of stops and frequency to minimize user and operator cost. The cost function for a route is defined in Eq. (6.1) (see Tirachini, 2014).

$$C_t = cf \left(\frac{L}{v_0} + \frac{\beta N}{f} + St_s \right) + P_a \frac{L}{2v_w S} N + P_w \frac{1}{2f} N + P_v \frac{l}{L} \left(\frac{L}{v_0} + \beta \frac{N}{f} + St_s \right) N \quad (6.1)$$

where c (\$/bus-h) is a unit bus operating cost, v_0 (mph) is bus operating speed, f (bus/h) is bus frequency, $t_c = \frac{L}{v_0} + \frac{\beta N}{f} + St_s$ (h) is the bus cycle time, β (sec/pax) is average boarding and alighting time per passenger, N (pax/h) is passenger demand, S is number of stops, t_s (h) is stopping delay, P_a (\$/h) is the value of access time, v_w (mph) is the walking speed, P_w is value of waiting time, P_v is value of in-vehicle time, and l is average travel distance (mi) per passenger. By jointly solving for (S^*, f^*) to minimize total cost, one can find the stop spacing and frequency to serve a route. Since solving them jointly is nonlinear, we discretized values of f to the nearest 0.1 increments, and optimized S^* . The optimum number of stops for a given frequency is obtained by taking the derivative of the cost with respect to number of stops, shown in Eq. (2.5). The value of f^* was found from the lowest total cost across all values of f .

An illustration of the operating cost for different values of frequency and number of stops for the B63 line with 800 passengers is shown in **Figure 6.2**.

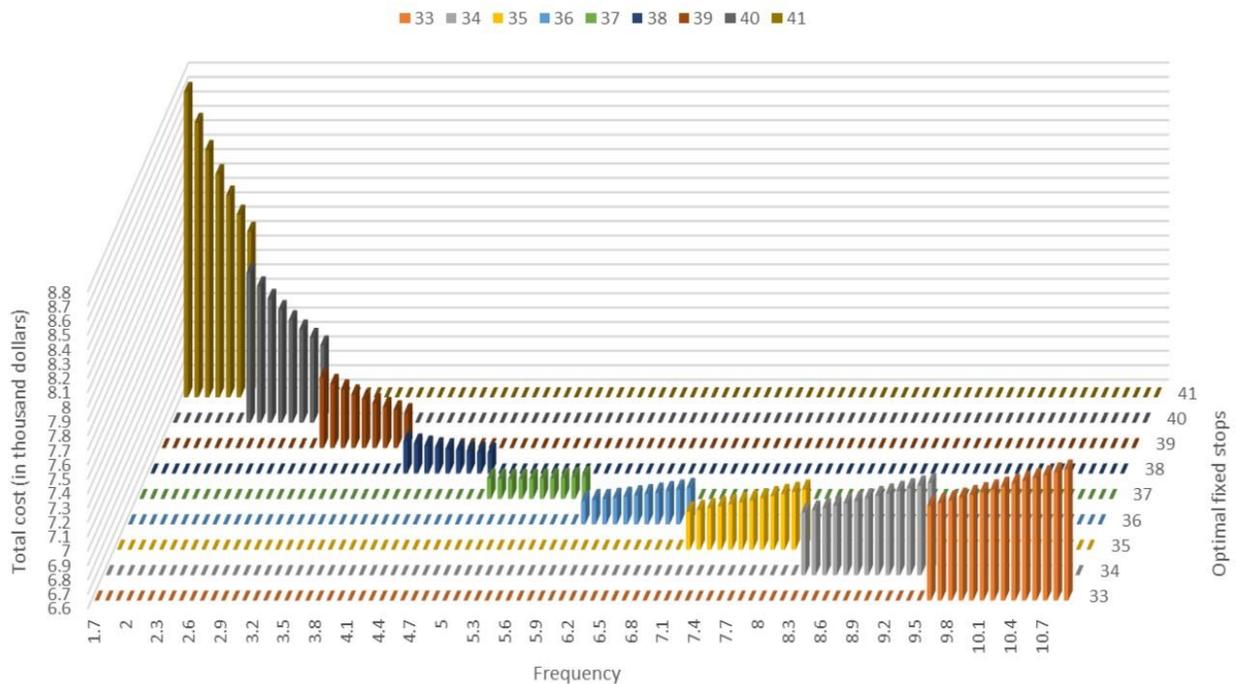


Figure 6.2. Total cost (\$000/h) as a function of frequency and optimal number of stops.

6.2.2. Flexible route policy

The flexible route policy is based on a combination of different efforts in this area, namely the insertion heuristic (Quadrifoglio et al., 2007) used for the MAST policy from Quadrifoglio et al. (2006), but expanded to consider (1) matching passengers to multiple candidate vehicles instead of just one, and (2) allowing passengers to walk further to a checkpoint or a route to be matched.

The service area in this setup consists of S_c checkpoints with 2 end checkpoints being the terminals and $S_c - 2$ intermediate checkpoints evenly distributed along the base route. Each vehicle visits all the checkpoints to serve requests located at checkpoints and deviates from the route to serve on-demand passenger requests located outside checkpoints within the service area and depending on having enough slack time. The pick-up customers show up at random origin locations within the service area with corresponding drop-off requests located at random in the rectangular region. Given the pickup and drop off locations, four different types of passengers' requests are considered:

- PD (“regular”): pick up and drop off at the checkpoints.
- PND (“hybrid”): pick up at the checkpoint, drop off not at the checkpoint.
- NPD (“hybrid”): pick up not at the checkpoint, drop off at the checkpoint.
- NPND (“random”): pick up and drop off not at the checkpoints.

The four types of passengers have their respective proportions $\alpha_1, \alpha_2, \alpha_3,$ and α_4 (such that $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$).

The service deviation is provided on a first come first serve basis. Moreover, the deviation follows a rectilinear path i.e., the vehicle is restricted to move either in a horizontal or vertical manner; a similar assumption is considered for passenger movement as well. The slack time allotted to the vehicle (t_{slack}) is a crucial parameter in allowing deviation from the base route. If t_{slack} is not utilized by deviation services, it becomes the idle time at the downstream checkpoint until the departure time at the respective checkpoint. On the other hand, if t_{slack} is exhausted, the system does not allow deviations to serve new incoming requests. Each stop in the flex-route component has an associated departure and arrival times. While there is a fixed schedule for the departure times at the checkpoints, the departure times at the non-checkpoint stops and all the arrival times are variables in the system.

Depending on the request times (i.e., time when a request is made) and the arrival times of the vehicle, each passenger must wait for a certain amount of time. In our setup, if the wait time for NP passengers (i.e., NPD and NPND type) is more than the walk time to their nearest checkpoint, such passengers can walk to the nearest checkpoint. In such cases, the NPD and NPND passenger type in our simulation model are treated as PD and PND type respectively. This is described using **Algorithm 6.1**.

Algorithm 6.1. Extended MAST insertion with passenger walking and multiple vehicles

Input: $L, W, T, t_d, v_o, v_w, U, V, K, h, S_c, t_c, \zeta_a, \zeta_b, \zeta_w$

Initialization: Locate S_c checkpoints evenly distributed along fixed route and define the specification of vehicle i where $i \in V$ (K, v_o , initial routes in both direction (from Checkpoint 1 to S_c and vice versa), travel time ($t_t = \frac{L}{S_c - 1} \frac{1}{v_o}$) and slack time ($t_{slack} = \frac{t_c}{S_c - 1} - t_t - t_d$) between checkpoints, and dispatch time ($\tau_{di} = (i - 1)h$)). $i_{max} = 0$.

For $\tau = 1, 2, \dots, T$ do

1. Dispatch vehicle i when $\tau = \tau_{di}$, $i_{max} = i_{max} + 1$.
2. If there are services requests from passenger $j \in U$, go to the next step. Otherwise, go to Step 13.

For $i = 1$ to i_{max} do

[Direct service]

3. Recall information of i including existing route r_i according to the identified direction of passenger j travelling.
4. Calculate expected wait and in-vehicle time of passengers assigned to i , t_{slack} for each section between checkpoints, and performance measure.

For $k_1 = 1$ to $|r_i|$ do

For $k_2 = k_1 + 1$ to $|r_i| + 1$ do

5. Insert O_j at the k_1 -th sequence of r_i and D_j at the k_2 -th place to create r_i^* .
6. Investigate the feasibility (the violation of K , t_{slack} , and ζ_b). If feasible, calculate updated expected wait and in-vehicle time of passengers and performance measure. Otherwise, try the next set of k_1 and k_2 .

Next

Next

7. Choose r_i^* with the minimum impact on performance measure as a feasible candidate route r_{id}^* . If there is no available route, i cannot directly serve j .

[j -walking]

8. Identify segments r_i which j can access from O_i and egress to D_j within ζ_a and determine potential intersections s_i where to approach (start/mid/end point).

For $k_3 = 1$ to $|s_i|$ do

9. Create r_i' by inserting k_3 -th intersection to r_i , and calculate the impact on expected wait and in-vehicle time of passengers and performance measure.
10. Investigate the feasibility (the violation of K , t_{slack} , ζ_b , and ζ_w). If feasible, calculate updated expected wait and in-vehicle time of passengers and performance measure. Otherwise, try the next k_3 .

Next

11. Choose r_i' with the minimum impact on performance measure as a feasible candidate route r_{iw}^* . If there is no available route, j cannot be assigned to i .

Next

12. Assign the passenger to either r_{id}^* or r_{iw}^* with the minimum impact of the performance measure. Update information of i and j . If there is no available i , send j to the rejected passenger set U_r .

[Resurrection of rejected passengers j_r]

13. If $|U_r| > 0$, repeat from Step 3 to 12 only for j_r who reach every 30 sec after their rejection except for ones added in this time step.

[Vehicle relocation]

For $i = 1$ to $|V|$ do

14. If vehicle is at a stop, determine whether a vehicle stays more or leaves a stop based on remaining dwell time. If there are additional passenger in this time step, process them.

15. If vehicle is moving, determine whether a vehicle keeps moving or arrives at a stop based on remaining distance. When arriving, process passengers waiting for being picked up or dropped off.

Next

16. If time step does not reach simulation period, go back to Step 1. Otherwise, go to Step 1.

Next

17. Aggregate simulation outputs.

6.2.3. Door-to-door service policy

The door-to-door service policy adopted for this case study is a simple insertion algorithm as shown in the literature for dynamic routing of flexible transit services (Gendreau et al., 1992; Berbeglia et al., 2010; Chow and Liu, 2012; Jung and Jayakrishnan, 2014). Every time a new passenger makes a request, the system evaluates every vehicle in the fleet. For each vehicle, it determines the best routing sequence using an insertion heuristic to determine the cost increase needed to serve that passenger with the vehicle, keeping in mind capacity and detour limit constraints. After evaluating every vehicle in the fleet, the algorithm selects the vehicle that minimizes the cost increase to serve the passenger. Idle vehicles are assigned back to their depots. **Algorithm 6.2** is shown below.

Algorithm 6.2. Insertion heuristic for dispatching and routing on-demand vehicles

Input: $L, W, T, t_d, v_o, v_w, U, V, K, h, S_d, \zeta_w, \zeta_d$, vehicle distribution along depot μ_s

Initialization: Locate S_d depots evenly distributed along fixed route and define the specification of vehicle i where $i \in V (K, v_o, \text{empty routes,})$. The number of vehicles per depot n_s is defined by the discrete distribution μ_s where $\sum_s n_s = V$.

For $\tau = 1, 2, \dots, T$ do

1. If there are services requests from passenger $j \in U$, go to the next step. Otherwise, go to Step 8.

[Passenger assignment]

For $i = 1$ to i_{max} do

2. Recall information of i including existing route r_i .
3. Calculate expected wait and in-vehicle time of passengers assigned to i and performance measure.

For $k_1 = 1$ to $|r_i|$ do

For $k_2 = k_1 + 1$ to $|r_i| + 1$ do

4. Insert O_j at the k_1 -th sequence of r_i and D_j at the k_2 -th place to create r'_i .
5. Investigate the feasibility (the violation of K , ζ_d , and ζ_w). If feasible, calculate updated expected wait and in-vehicle time of passengers and performance measure. Otherwise, try the next set of k_1 and k_2 .

Next

Next

6. Choose r'_i as a feasible candidate route r_i^* with the minimum impact on performance measure. If there is no available route, i cannot serve j .

Next

7. Assign the passenger to r_i^* with the minimum impact of the performance measure and update information of i and j . If there is no available i , reject j .

[Vehicle relocation]

For $i = 1$ to $|V|$ do

8. If vehicle is staying at a stop, determine whether a vehicle stays more or leaves a stop based on remaining dwell time. If there are additional passenger in this time step, process them.
9. If vehicle is moving, determine whether a vehicle keeps moving or arrives at a stop based on remaining distance. When arriving, process passengers waiting for being picked up or dropped off.

Next

10. If time step does not reach simulation period, go back to Step 1. Otherwise, go to Step 1.

Next

11. Aggregate simulation outputs.
-

6.3. Data

The simulation with the specified operating policies in Section 6.2 is applied to a synthetic data set created from:

- An existing bus route, including its stop locations and timetable for a 4-hour period
- Stop-level origin-destination (OD) demand based on surveyed ridership

For the bus route, the B63 line running in Brooklyn, NY, is chosen, as shown in **Figure 6.3**. This line is operated by the NYC Metropolitan Transportation Authority along a fixed route mainly offering service between Bay Ridge and Cobble Hill in Brooklyn, NYC. The daily ridership for this route as of 2018 is 11,148 (MTA, 2020b).

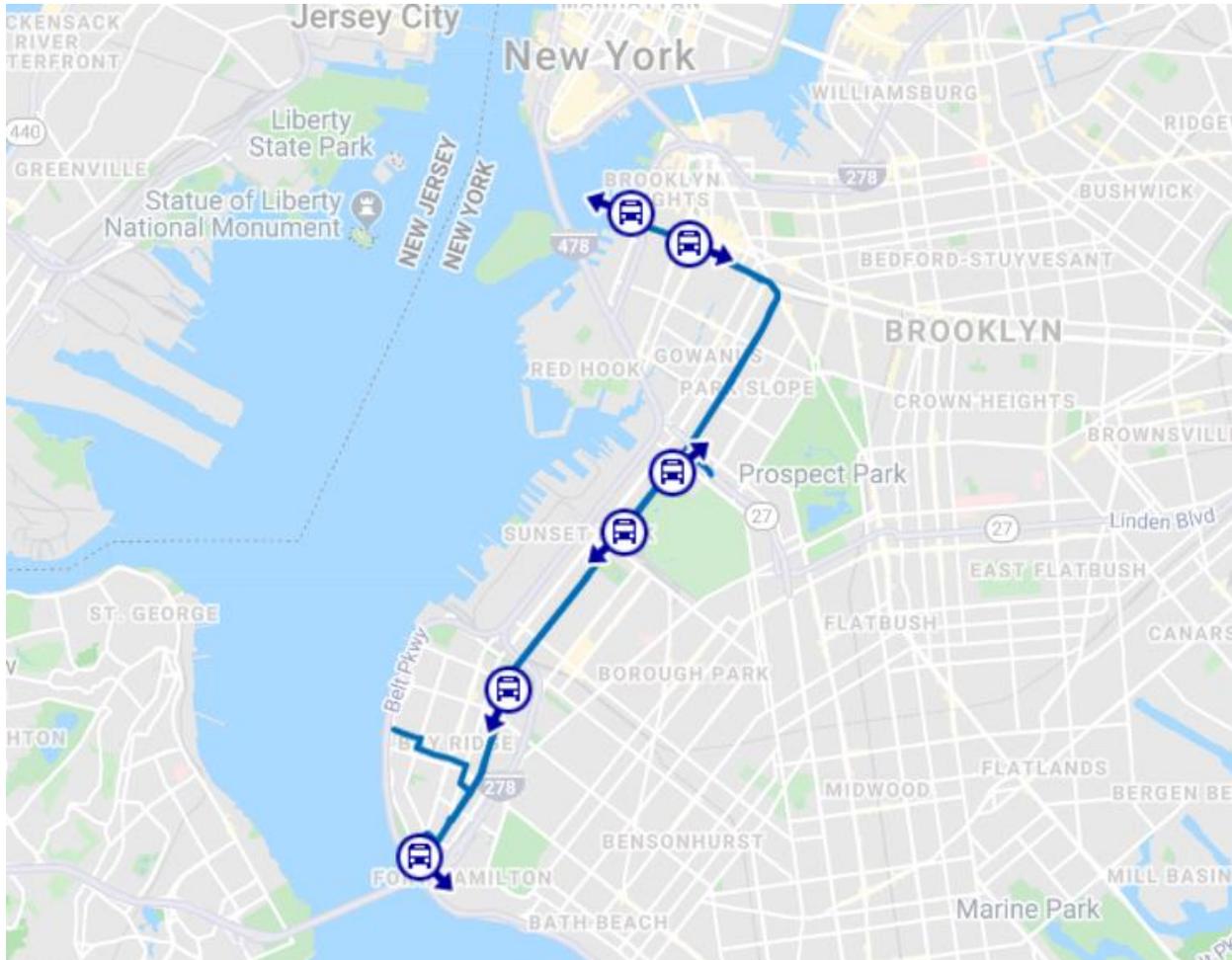


Figure 6.3. Real time feed of bus locations on B63 route (MTA, 2020a).

The simulation parameter values used for the B63 Brooklyn bus service are presented in **Tables 6.2** and **6.3**. The data used in this simulation consists of two different arrays shown in **Tables 6.4**. First, “Pax” indicates the information of potential passengers who requests for

service. Their x- and y- coordinates of origin and destination (OD) are randomly generated within the service area ($L \times W$), and the distance between OD should not be shorter than the walking distance limit (ζ_a) to prevent a situation that passenger waits for a bus although walking is definitely better travel option. The number of artificial passengers in this dataset is 30 times more than preset average arrival rate (λ), 80, 200, or 400 pax/h. Second, “numNewPax” represents the number of new requests for each time step. We set up the assumption that the number of service requests per time step follows Poisson distribution with λ . It can cover 100,000 time-steps (e.g. if a time step is a second, 100,000 sec \approx 28 hrs). These datasets are accessible via Zenodo¹¹. The distributions of the origins and destinations for the 400-passenger simulation are shown in **Figure 6.4**.

Table 6.2. Common parameters for all systems

Parameter	Value
Average demand level (pax/h)	80 (10% of peak hour), 200 (25%), 400 (50%)
Route length (mi) (L)	8.2 (Stringer, 2017)
Service area (sq. mi) (L×W)	8.2×1.0
Maximum walking distance (mi) (ζ_a)	0.5
Number of stops (S)	57 (including two terminals)
Average dwell time (t_d)	20 sec
Average vehicle running speed (v_o)	7.13 mph
Average peak hour frequency (f)	5 veh/hr (MTA, 2020b)
Time step	1 sec
Simulation length	4 hr
Walking speed (v_w)	3.1 mph
Maximum walk distance (ζ_a)	0.5 mi
Weight for passenger travel time ($\gamma_v, \gamma_w, \gamma_a$)	1 (in-vehicle time) / 1.59 (wait time) / 1.79 (access time) (Wardman, 2004)

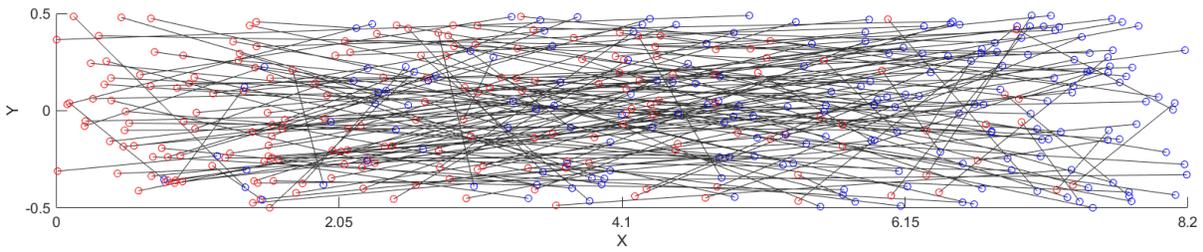
¹¹ <https://doi.org/10.5281/zenodo.3672151>

Table 6.3. System-specific parameters

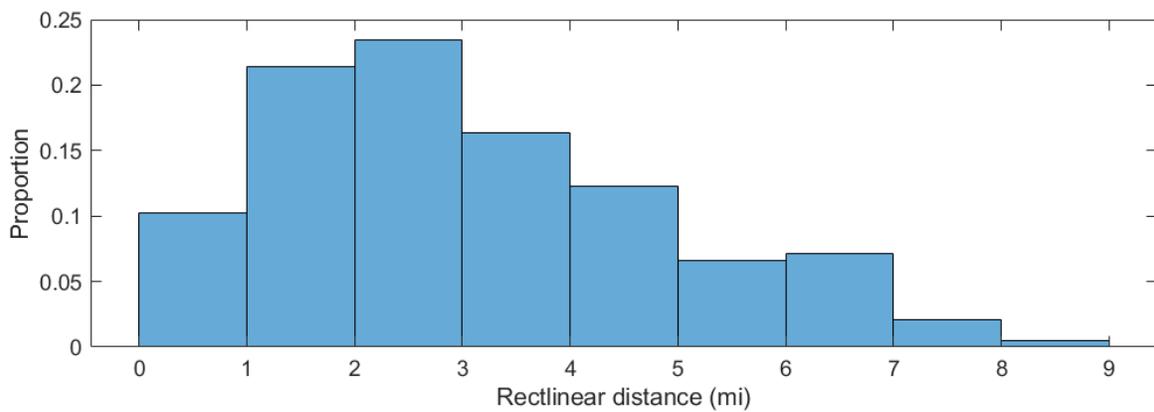
Parameter	Value		
	Fixed route	Flexible route	Door-to-door
Fleet size (V)	15	20	40
Predetermined headway (h)	12 min (for all stops)	12 min (for checkpoints)	
One-way cycle time (t_c)	88 min (Stringer, 2017)	120 min	
Number of fixed stops (S)	57 (two terminals)		
Number of checkpoints (S_c)		10 / 20	
Number of depots (S_d)			10
Vehicle capacity (K)	85 (MTA, 2019)	40	20
Max. detour time rate (ζ_d)			2 (prohibit ride time being twice longer than fixed route)
Max. wait time (ζ_w)		12 min	30 min
Max. backtracking distance (ζ_b)		0.25 mi	
Max. deviation distance ($\frac{W}{2}$)		0.5 mi	

Table 6.4. Data dictionary

Column	Data	Description
Data Dictionary for Pax		
1	Passenger ID	ID for passengers, given in a “First-come-first-served” scheme
2	OStop ID	Stop ID of passenger’s origin (empty, assigned during simulation)
3	OStop x	x-coordinate of passenger’s origin
4	OStop y	y-coordinate of passenger’s origin
5	DStop ID	Stop ID of passenger’s destination (empty, assigned during simulation)
6	DStop x	x-coordinate of passenger’s destination
7	DStop y	y-coordinate of passenger’s destination
8	HDist	Horizontal distance between OD
9	VDist	Vertical distance between OD
Data Dictionary for numNewPax		
1	numNewPax	Number of new requests



(a)



(b)

Figure 6.4. (a) Distribution of southbound 400-passenger scenario origins to destinations; (b) trip length distribution.

The other parameters of the simulation are taken from various sources like the MTA, Stringer, and Wardman. We also made assumptions about certain values (like dwell time, coverage distance from line, walking speed, and thresholds for the operating policies like maximum wait times and detour times).

The simulation is run for the following **fifteen scenarios**:

- Five policies: fixed route (existing number of stops and frequency), fixed route (the stops and frequency set from Section 6.2.1), flexible route (20 checkpoints), flexible route (10 checkpoints), and door-to-door, as specified
- Three demand levels: 80, 200, and 400 pax/h

6.4. Results

The simulation results are shown in detail below. **Table 6.5** shows the realized ridership which considers rejections due to the on-demand operating policies having thresholds. Ridership goes down a bit for door-to-door under the 200 and 400 pax/h scenarios because the fleet size assumed (40 vehicles) is insufficient capacity to cover the demand.

Table 6.5. Simulated ridership

Demand	Fixed	Optimized Fixed	Flexible ($S_c=20$)	Flexible ($S_c=10$)	Door-to-door
80 pax/h	333	331	314	314	318
200 pax/h	791	791	753	666	586
400 pax/h	1625	1622	1546	1192	766

Tables 6.6 – 6.8 show the simulated wait time, in-vehicle time, and walk time for each scenario, respectively. **Table 6.9** shows the weighted travel times reflecting the passengers’ perceived user costs. **Table 6.10** shows the total vehicle mileage. While the user costs for the “optimized” fixed route are worse than the existing scenario, the operating cost is significantly lower. This makes sense since the optimization considers both user and operator costs.

The flexible route service has similar wait times to the existing fixed route, and lower wait times than the optimal fixed route, but higher in-vehicle times and only slightly lower walk times. These differences can be adjusted further by altering the flexible route service parameters like number of checkpoints and thresholds. The flexible route operating miles are much higher relative to the optimal fixed route policy, although that does not consider operating and capital costs of smaller buses used by the flexible route service.

The door-to-door has worse wait time (due to the low fleet size) but negligible walk times. As a result, it has the lowest user costs, but the operating miles are significantly higher than the other policies and need to be offset by lower operating and capital costs per vehicle. Depending on the costs, one can see that the three types of policies can thrive under different ranges of demand density. The tool allows a reader to evaluate such alternatives.

Table 6.6. Simulated wait time

Demand	Fixed	Optimized Fixed	Flexible ($S_c=20$)	Flexible ($S_c=10$)	Door-to-door
80 pax/h	5.14	12.52	4.55	5.87	14.09
200 pax/h	5.27	10.97	4.66	6.01	18.94
400 pax/h	4.90	7.38	5.08	6.27	19.68

Table 6.7. Simulated in-vehicle time

Demand	Fixed	Optimized Fixed	Flexible ($S_c=20$)	Flexible ($S_c=10$)	Door-to-door
80 pax/h	28.95	28.58	38.68	39.26	26.48
200 pax/h	28.61	28.08	37.85	38.18	25.99
400 pax/h	29.04	28.53	38.32	38.62	23.97

Table 6.8. Simulated walk time

Demand	Fixed	Optimized Fixed	Flexible ($S_c=20$)	Flexible ($S_c=10$)	Door-to-door
80 pax/h	11.10	12.43	11.98	11.45	0.00
200 pax/h	11.06	12.33	12.22	13.15	0.00
400 pax/h	11.20	12.16	12.72	14.53	0.00

Table 6.9. Simulated total weighted travel time

Demand	Fixed	Optimized Fixed	Flexible ($S_c=20$)	Flexible ($S_c=10$)	Door-to-door
80 pax/h	58.86	72.22	69.46	70.97	47.61
200 pax/h	58.63	69.19	69.27	73.48	54.40
400 pax/h	58.78	63.93	71.38	77.09	53.49

Table 6.10. Simulated total vehicle mileage

Demand	Fixed	Optimized Fixed	Flexible ($S_c=20$)	Flexible ($S_c=10$)	Door-to-door
80 pax/h	335.72	137.73	339.69	391.08	772.10
200 pax/h	335.72	160.71	349.10	419.32	1005.31
400 pax/h	335.72	228.80	362.93	423.41	1072.54

The key performance measures are shown in figures below. **Figure 6.5** shows the ridership in each scenario. The lower checkpoints in flexible route leads to increased instances of trip rejection as the demand goes up since more trip slack time gets consumed. The fleet size for door-to-door is insufficient to handle the increased demand, leading to many more rejections under the designed maximum wait time threshold. **Figure 6.6** shows the weighted travel times representing user costs. The optimized fixed route service improves user cost as density goes up while the other policies remain relatively the same. **Figure 6.7** shows the total vehicle miles traveled, which increases with demand in all cases except the existing fixed route (since that doesn't change across demand scenarios).

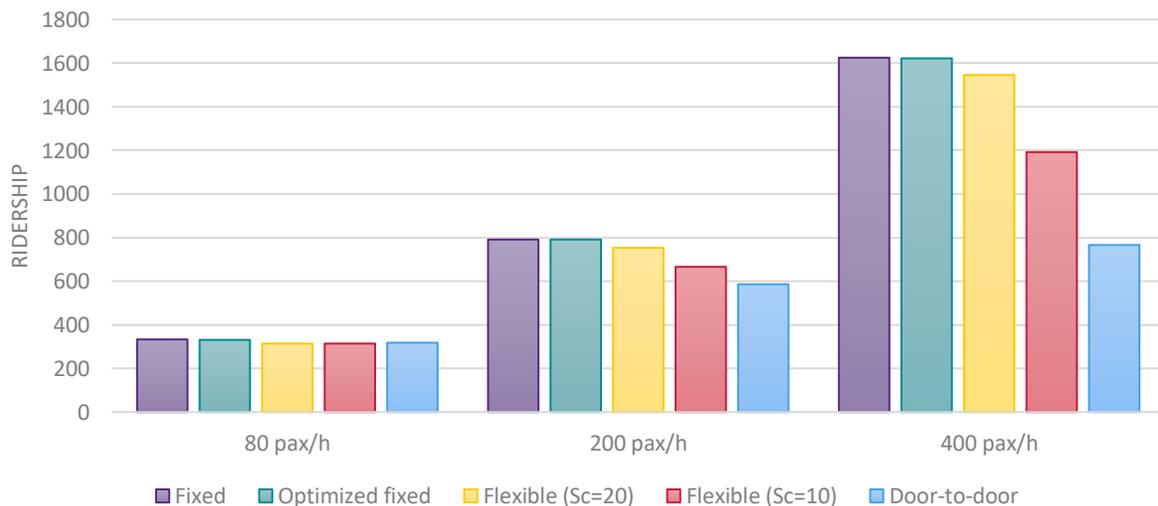


Figure 6.5. Simulated ridership.

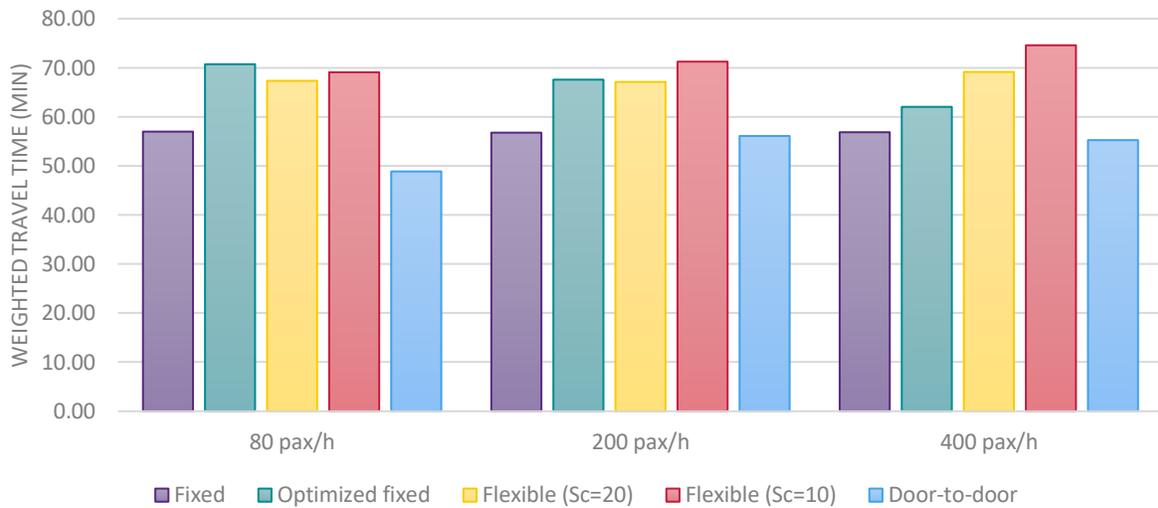


Figure 6.6. Simulated weighted travel time.

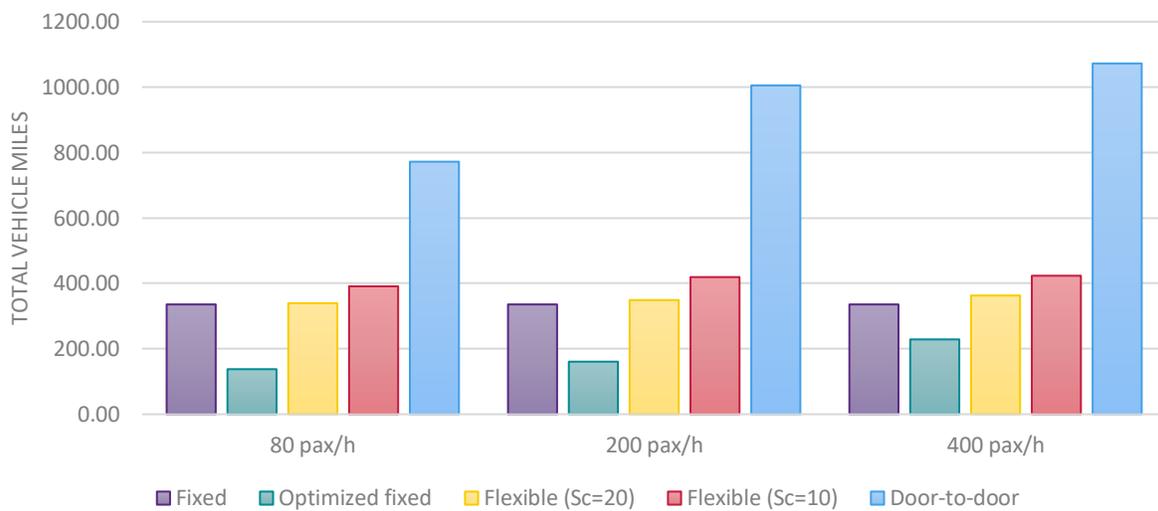


Figure 6.7. Simulated total vehicle miles traveled.

6.5. Tech transfer

The case study demonstrated in Section 6 is meant to illustrate how one can analyze a study area using existing data sources. In our case, the B63 line in Brooklyn, NY, is used. However, the code and data are both provided in open data repositories linked from this

compendium. Readers are welcome to try out the simulation for their own transit lines to see how other operating policies work.

There are several ingredients to setting up a comparison in a new study area beyond Brooklyn.

- Determine passenger arrivals. In our case study we randomly generated the arrivals. However, these can be hardcoded into a list of synthesized arrival locations and times using observed arrivals.
- System parameters. If the analysis is applied to an existing line, the characteristics of that line can be used to determine the physical aspects like line length, vehicle speeds, etc. The operating policy (frequency, stop spacing) can also be set the same as the existing line or be defined separately.
- The thresholds can be adjusted to other values (large enough thresholds would be “ignored”). If other operating policies are desired, they need to replace the dispatch/routing algorithms in the simulation, i.e. **Algorithms 6.1** and **6.2**.
- The simulation should have a warmup time.
- All policies need to consider fleet size. For fixed route this is implied by the frequency, but for the other two policies it needs to be specified carefully.
- Flexible route service needs to consider checkpoints, slack time, maximum wait time threshold, and maximum backtrack distance.
- Door-to-door service needs to consider allocation of idle vehicles. Other more advanced idle vehicle relocation policies can be assumed as well.

Section 7: Conclusion

In this compendium, we had two primary objectives. The first was to provide an up-to-date literature overview of the spectrum of public transit operations from fixed route service to real-time, on-demand microtransit. This objective considers trends, technologies, and governance barriers as well. The second objective was to create a replicable data set and simulation that can be used to evaluate a transit line under different operating policies. Both objectives combine to provide a toolset for readers to help them transfer these technologies to their localities. The intent is not so much to study what is the impact of the policies on the B63, but to take that example and modify from it to other locations to evaluate the potential of the service there.

As a result of the synthesis, several lessons are learned from which we provide recommendations to address obstacles to incorporating real-time route adjustments. These are summarized along the following dimensions.

7.1. Technological recommendations

Given the availability of various transit apps on mobile phones for providing timely and accurate information to riders, and the development of new technologies for acquisition of real-time users' data and systems data, the information flow between the transit system and users can certainly improve the attractiveness, reliability and efficiency of transit services. Real-time updates on vehicle location, vehicle arrival times, delays and disruptions enable commuters to make better decisions, reduces their wait times, and makes the service more reliable; a better service quality can boost ridership and revenue.

A combination of multiple types of real-time information on passenger counts, traffic status, road conditions, and system performance can be used by traffic operators in deciding the operations, network planning, scheduling and control of vehicles under dynamic environment (using appropriate open source tools discussed in the compendium). Some

strategies may include planning dynamic and automated vehicle dispatching system, developing schedules responding to user demand, adjusting headway and frequencies as per passenger load patterns, implementing vehicle operation control and holding strategies, monitoring service quality, and coordinating with ITS technology for signal prioritization for transit vehicles. The real-time information on demand and supply side can be used effectively for adjusting the service and for managing the demand.

In terms of demand management, differential fare pricing policies such as off-peak discounting, increased peak fares, combination of surcharge and discounts, passenger rewards, or incentive-based fare schemes could be implemented. Low cost automated data collection technologies could be used to quantify the impacts of different schemes and design on travelers' behavior and the ridership, and to evaluate the potential savings and revenue from improvements in service planning and operations.

As we move towards a future that will bring the automated, electrified and shared mobility together, transit agencies will need to incorporate these components in the network design and operations planning of the transit system. The objective will be more oriented towards sustainability in case of electric vehicles (EV) while intelligent approaches need to be adopted for better coordination in case of autonomous vehicles (AV). Electrification of transportation system has numerous advantages including reduced fuel and maintenance cost, increased price stability, and reduced noise and air pollution. However, for large-scale deployment of EVs, the battery life, vehicle power, performance of EVs during extreme weather conditions, energy requirements, and investment on energy storage are important factors that need to be considered for infrastructure planning and EV fleet management. While improved service reliability, increased frequency, and reduced journey times are expected with use of AVs, understanding the potential of different levels of automation technology and their impact on public transit is crucial. Assuming that the automation technology reaches a certain degree of development allowing for reduction in operating costs, there could be significant reduction in fare and subsidy per trip, along with reduced waiting times. Besides technology deployment for

AVs, issues on safety, regulations and policies need to be considered in the planning process as well.

Testing of technologies needs to be more readily available. Due to the diverse breadth of operating strategies and service patterns, there should be more efforts made to create a **common repository of publicly accessible simulation scenarios across different cities** that make use of common performance metrics so that new operating strategies can be evaluated across all these cities. A certification process can be created and endorsed by the U.S. DOT and affiliated research institutions to allow technology providers and policymakers to evaluate their proposed policies/systems across these common simulation scenarios, so that as an outcome one can say their policy has gone through certification and shows an appreciable improvement in performance measures against some predefined benchmark.

7.2. Infrastructural recommendations

Depending on the network structure and service design of the transit system, the transit agencies can quantify the capacity elements required for spatial structures (road links) as well as non-spatial queuing structures (parking facilities or pickup/drop-off platforms) using appropriate methods discussed in the compendium. In addition to network design, service components such as type and capacity of service vehicle, fare collection method, frequency and flexibility of service, and real-time information to users greatly influence the infrastructure planning for different transit operations as these components directly impact the number of waiting passengers, and boarding delays.

The models that can be used by the traffic operators in designing a suitable and cost-effective flexible transit system in any environment may include quantitative techniques for calculating capacity elements and other operational characteristics of the system, strategies for prioritization and coordination of bus-only lanes with traffic signal system, methods for flexible

space allocation between passenger cars and buses, and models to evaluate trade-offs between demand and capacity.

Road space usage in the literature suggests a wide range of options, whether it's dedicated lanes for buses, bikes, and parking (passenger cars or shared vehicles); and curb space management to allow virtual bus stops for flexible route transit and on-demand microtransit. We recommend that a **national curbside management benefits database** be setup, similar to how the ITS Benefits Database provides compilations of case studies with data and performance measures.

7.3. Market dynamics recommendations

The major finding from the review of market dynamics is that there are already efforts toward integrating different mobility operations under single platforms as MaaS. The difference is whether these platforms are driven by private providers or public agencies, resulting in different contract practices. Data sharing remains a deterrent to the development of MaaS, despite efforts to add data sharing standards like the Mobility Data Specification, because it requires incentives from operators to participate. In addition, operators need evidence that multimodal trips are viable but for now there does not exist any publicly available source of data of travelers' multimodal route choices. As such, to better understand market dynamics, we recommend a major study effort to **collect publicly accessible multimodal travel data** in one of the pilot sites that already have multimodal operations in place. This needs to be traveler-oriented data; operator-oriented data (e.g. Uber pickups and drop-offs, or transit smart card tap ins and tap outs) do not provide the full picture of a traveler's journey.

7.4. Governance recommendations

The performance of a system depends on the regulatory environment. The comparison of the three operational strategies in the Brooklyn case study may not reflect the same results when we consider it in San Diego, CA, or El Paso, TX. This is because even among different local governments the regulatory environments can be different.

Recommendation along this dimension follows the technological recommendation in Section 7.1. We recommend a common repository of publicly accessible simulation scenarios across different cities. To account for governance, it is important to include **tagging of regulation types** in each city simulation. For example, NYC has dedicated bike lanes and allocated parking spaces for carshare. These regulations should be tagged for the NYC simulation. Over time, once many different city simulations are available, it will be easy to query performance metrics by type of regulation.

7.5. Next steps

This compendium is a starting point for other efforts. The simulator can be applied en-masse to all transit lines in the U.S. to output performance metrics throughout so that relationships can be established between different local built environments, their regulatory and institutional settings, and investment levels with performance metrics under different types of operating policies.

The simulator would also benefit many communities in which no transit service exists to help design an appropriate service. This requires a combination of surveying the public and making use of any forecast model that can be derived/calibrated from the existing line data.

The simulator can be extended to cover more policies, especially with electrification and automation. The line-level evaluation can be extended to a network level evaluation.

Lastly, this compendium points to the need for a knowledge base in the U.S. for demand-responsive transit operations. While there are centers that cover shared use mobility and transit, they tend to focus on policy. There needs to be an institution for the study of the spectrum of transit operations from fixed route to microtransit, and all their related impacts.

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