Simulating Semi-on-Demand Hybrid Route Transit Feeders with Shared Autonomous Mobility Services

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Short summary

This study simulates transit feeder services in semi-on-demand hybrid route, integrating fixed-route efficiency with demand-responsive flexibility, operated by shared autonomous vehicles (SAVs). Adapting the simulation framework FleetPy, we assess its performance against traditional fixed and flexible routes on a bus route in Munich, Germany, focusing on cost and service quality. The findings reveal the hybrid model's potential to improve service accessibility and journey times, contingent on the fixed-flexible route balance. It evaluates the stochastic effects on waiting and riding times due to the on-demand portion, and the optimal settings of route form, fleet size, and headway.
Keywords: simulation, public transport, semi-on-demand, feeder, shared autonomous vehicles

1 Introduction

Background

The emergence of shared autonomous vehicles (SAVs) presents both challenges and opportunities for enhancing public transportation networks Pinto et al. (2020); Dandl et al. (2021); Ng, Mahmassani, et al. (2024). In particular, SAVs have been identified as potentially effective first-mile-last-mile feeder services in low-density areas Grahn et al. (2023); Klinkhardt et al. (2023). Scenarios characterized by directional demand, such as transit feeders, can enable more efficient fixed-route operations compared to standard ride-hailing or ride-pooling services. Studies (e.g., Ng & Mahmassani, 2023; Ng, Dandl, et al., 2024) explored the application of SAVs in a semi-on-demand hybrid route (Figure 1), which combines the economy of scale of fixed-route buses with the flexibility of demand-responsive transit. In the fixed route area (generally higher density), SAVs operate like a scheduled bus service; in the flexible route area, they offer on-demand pick-ups and drop-offs akin to ride-pooling. This service minimizes journey times (including access times), providing passengers with flexibility and schedule predictability.

Literature review

The literature on on-demand transit is extensive as previously reviewed by Ng & Mahmassani (2023) and Ng, Dandl, et al. (2024), with comprehensive surveys by Errico et al. (2013) and Vansteenwegen et al. (2022) on recent advances in demand-responsive systems and by Narayanan et al. (2020) on shared autonomous vehicles.
Simulation is often used as a tool to gain insights into operational aspects of demand-responsive services. Several transportation models have been extended in recent years to simulate both fixed- and flexible-route services, e.g. SUMO (Armellini, 2021), MATSim (Horni et al., 2016), and Polaris (Gurumurthy et al., 2020; Cokyasar et al., 2022). Additionally, several studies built new agent-based simulation models for demand-responsive services, usually focusing on operational aspects or better computational performance without traffic simulations (e.g., Alonso-Mora et al., 2017; Fagnant & Kockelman, 2018; Dandl et al., 2019; Engelhardt et al., 2022) or with Macroscopic Fundamental Diagrams (Alisoltani et al., 2020; Beojone & Geroliminis, 2023).
Rich et al. (2023) conducted a comparative analysis of fixed-route and demand-responsive methods as feeder services for light rail transit, using agent-based simulation. Collectively, previous studies

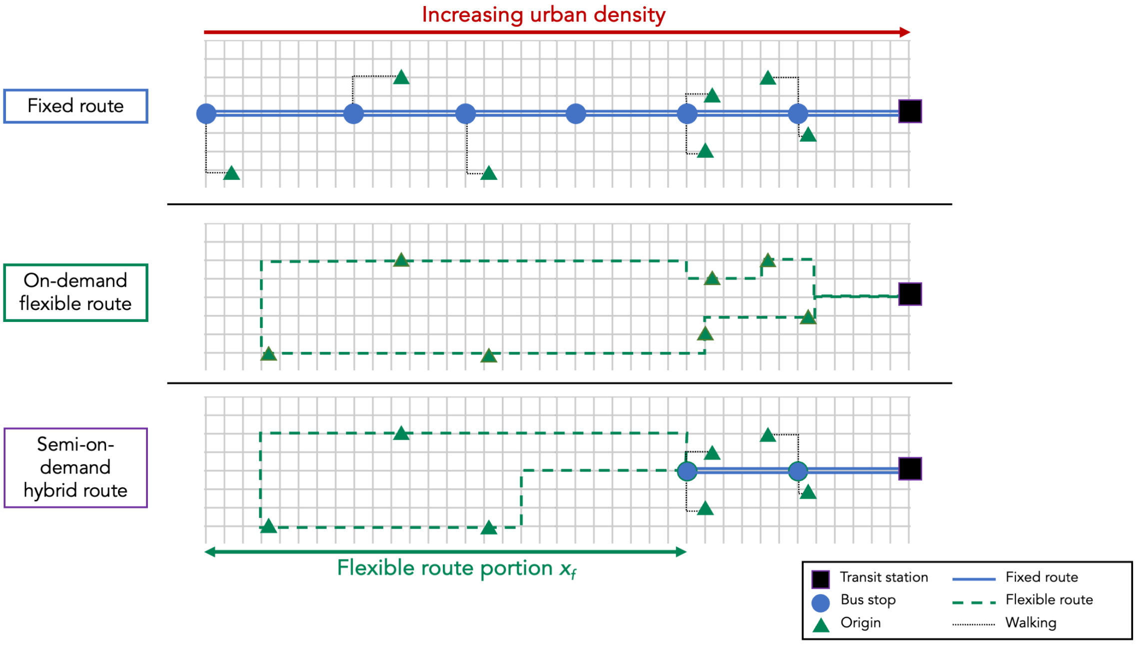

Figure 1: Illustration of fixed route, on-demand flexible route, and semi-on-demand hybrid route as a feeder service

primarily focus on the performance of flexible-route service or on the decision to deploy either flexible-route or fixed-route services. In contrast, this study builds on (Ng, Dandl, et al., 2024) and simulates the hybrid route service, which represents a continuum between these two service modes, defined by the extent of the flexible route portion.

Motivation and objective

Drawing on the analytical frameworks developed by Ng & Mahmassani (2023) and Ng, Dandl, et al. (2024), this study aims to validate the performance of semi-on-demand hybrid route feeder services using real-world demand data on a bus route in Munich, Germany. As the service forms of hybrid routes span between fixed and flexible routes, the study also compares the performance and cost across all three kinds of routes, in terms of costs (users' and operator's) and journey time. With Monte Carlo simulation, confidence intervals are constructed for key metrics to understand the result robustness and experience discrepancy among users. The costs are compared with the theoretical formulation (Ng, Dandl, et al., 2024) to evaluate the effects of assumptions such as ignored demand and operation variance. We also evaluate the optimal route form (and flexible route portion for hybrid route), fleet size, and headway based on simulation results with an SAV fleet.

In short, the contributions of this study are three-fold:

1. Empirical validation of benefits and performance of hybrid route services
2. Investigation of stochastic effects on waiting and riding times of passengers and operator's costs for hybrid routes
3. Exploration of hybrid route design including optimal route form, fleet size, and headway in existing transit line cases

2 Methodology

This study employs FleetPy, an agent-based SAV simulation framework (Engelhardt et al., 2022), to analyze the operation of a semi-on-demand hybrid route transit line. The tool is adapted to cater to the proposed service form in public transport schedules and request handling.

Public transport schedule setting

The key design variables of the hybrid route service include the flexible route portion x_f, fleet size s, and headway h. A loop route is assumed for a hybrid route, i.e., SAVs departing from a terminus, calling at fixed stops, and then serving on-demand requests in the flexible route portion before returning to scheduled fixed stops and finally the terminus. A detour factor ϕ sets the upper bound for detours in the flexible route portion, thereby determining the scheduled fixed-route stop times for the return trip. The original round trip time t_r is therefore adjusted to t'_r that includes additional time reserved for detours in Eq. 1, where t_d is the journey time originally scheduled for stops in the flexible route portion.

$$t'_r = t_r + \phi t_d \tag{1}$$

For a feasible schedule, sufficient vehicles must be provided to fulfill the headway and journey time requirement after accounting for detours in Eq. 2, where t_t is the turnaround time at a terminus.

$$s \geq (t'_r + t_t)/h \tag{2}$$

Afterward, the minimum feasible number of vehicles is deployed to minimize the vehicle marginal cost.

SAV fleet simulation and control

The simulation consists of three agents: Customers (1), requesting trips from the service operator (2) which assigns schedules to its vehicles (3) to serve the customers by moving in a street network $G = (N, E)$ with nodes N and edges E. A customer request r_i is defined by its request time t_i, its origin $o_i \in N$, and its destination $d_i \in N$. A schedule consists of an ordered list of stops that are processed by the vehicle one after another. A stop s, in fixed and flexible portions, is characterized by a location $y_s \in N$, the latest start time l_s, the earliest start time e_s, and a duration d_s. Additionally, each stop is associated with a list of boarding and alighting customers. In between stops, vehicles $v \in V$ travel in the network on the fastest route. If they arrive at the next stop s before e_s, they wait until e_s. In the next step, they perform the boarding task associated with this stop for a duration of d_s and continue with driving to the consecutive stop afterward.
At the beginning of the simulation, each vehicle is initialized with its corresponding fixed line schedule for the whole simulation period. Thereby, e_s and l_s are set to the scheduled arrival time at each fixed-route bus stop y_s. During the simulation, new customers request trips in each simulation time step of $60s$. In each time step, the operator assigns requests iteratively with the following steps:

1. If a customer request $r_i = (t_i, o_i, d_i)$ is picked up or dropped off in the fixed portion, o_i or d_i is shifted to o_i^F or d_i^F corresponding to the nearest bus stop of o_i and d_i, respectively.
2. A request is assigned to the vehicle schedule by:
   - adding the request to the boarding or alighting list of a stop if the corresponding locations match; or
   - inserting a new stop to pick up or drop off the request.

   An insertion is feasible if and only if:
   - each stop s in the schedule can be served before l_s elapsed;
   - each customer served by the schedule is picked up before a maximum waiting time $t^{W,max}$ elapsed;
   - the maximum in-vehicle travel time of each customer served by the schedule does not exceed the shortest path time t^S by a factor ϕ^P; and
   - at no time more than c_v customers are on-board of the vehicle.

   All feasible insertions for a request and each vehicle are computed by an exhaustive search, and the schedule ψ that minimizes the objective in Eq. 3 is assigned, where γ_v^O, γ^R, γ^S, and γ^F are respectively the cost/reward coefficients for vehicle distance, traveler time, requests satisfied, and requests served in a fixed route, and $d_{v,\psi}$, $a_{i,\psi}$, n_ψ^S, and n_ψ^F are respectively the distance traveled by a vehicle v, arrival time of passenger i, number of requests satisfied, and number of requests served in a fixed route.

$$\rho(\psi) = \sum_{v \in V} \gamma_v^O d_{v,\psi} + \sum_{i=1}^{N^R} \gamma^R (a_{i,\psi} - t_i) - \gamma^S n_\psi^S - \gamma^F n_\psi^F \tag{3}$$

If no feasible insertion is found, the customer request is rejected.

3. Repeat Steps (1)-(2) until all customer requests are processed. Then, vehicles move and perform boarding processes according to their assigned schedules.

Cost computation

Following the cost definition by Ng, Dandl, et al. (2024), this subsection summarizes the cost components. The user cost c_i^U of rider i in Eq. 4 is composed of access (walking), waiting, and riding costs, where t_i^A, t_i^W, and t_i^R are the access, waiting, and riding times and γ^A, γ^W, and γ^R are the cost coefficients for access, waiting, and riding times.

$$c_i^U = \gamma^A t_i^A + \gamma^W t_i^W + \gamma^R t_i^R \tag{4}$$

The vehicle cost c_v^O for vehicle v consists of distance-based operating cost and vehicle marginal cost, where d_v and t_v^V are the distance traveled and time deployed, and γ^O, and γ^V are the cost coefficients for operating distance and vehicle time.

$$c_v^O = \gamma_v^O d_v + \gamma_v^V t_v^V \tag{5}$$

The total generalized cost c^G in Eq. 6 is the sum of all users' costs and operator's costs.

$$c^G = \sum_{i}^{N^R} c_i^U + \sum_{v \in V} c_v^O \tag{6}$$

3 Results and discussion

Scenarios and data

As shown in Figure 2, the bus route 193 in Munich, Germany, serves as a feeder to underground and suburban rail at its terminus Trudering Bahnhof. Its route length is 5.61km with an assumed round-trip journey time of 33 min. The simulated time is from 9 pm to midnight with only the middle hour used to evaluate metrics from the simulation after warm-up and before cool-down.
Trip origins and destinations are derived from an adapted boarding and alighting dataset of a local public transport operator. The transit alignment and stop locations are extracted from the GIS data (Münchner Verkehrsgesellschaft, 2024). The road network information is obtained using OSMnx (Boeing, 2017).
Key parameters are as follows:$\gamma^R = \$16.5/h, \gamma^A = \$33/h, \gamma^W = \$24.75/h, \gamma^O = \$0.694/km, \gamma^V = \$7.59/h, \gamma^S = \gamma^F = 10^6, \phi = 1.4, t^{W,max} = 15min, \phi^P = 2, c_v = 20$ (monetary value in US dollars). SAV cost parameters are referenced from Tirachini & Antoniou (2020).
Monte Carlo simulations are conducted to simulate the feeder service under each scenario with 100 generated demand instances with resulting confidence intervals.

Simulation results

We first discuss the results of a baseline case with 10-minute headway in Figure 3 and Table 1 in the Appendix. The number of passengers served decreases with longer flexible route portions as shown in Figure 3(a). The metrics shown below account for the served passengers only. The average generalized cost per passenger in Figure 3(b) indicates the efficiency of the system, which reached its minimum at around 2km flexible route portion. In this scenario with high headway, excessive detour not only reduced the capacity to meet demand but also led to increased operational costs and additional riding time for passengers. Figure 3(c) illustrates the increasing detours incurred to the vehicle trips.
Figure 3(d) looks into the trade-offs between various passenger time metrics (in solid lines) in increasing flexible portion, also compared with the theoretical values assuming a uniform demand

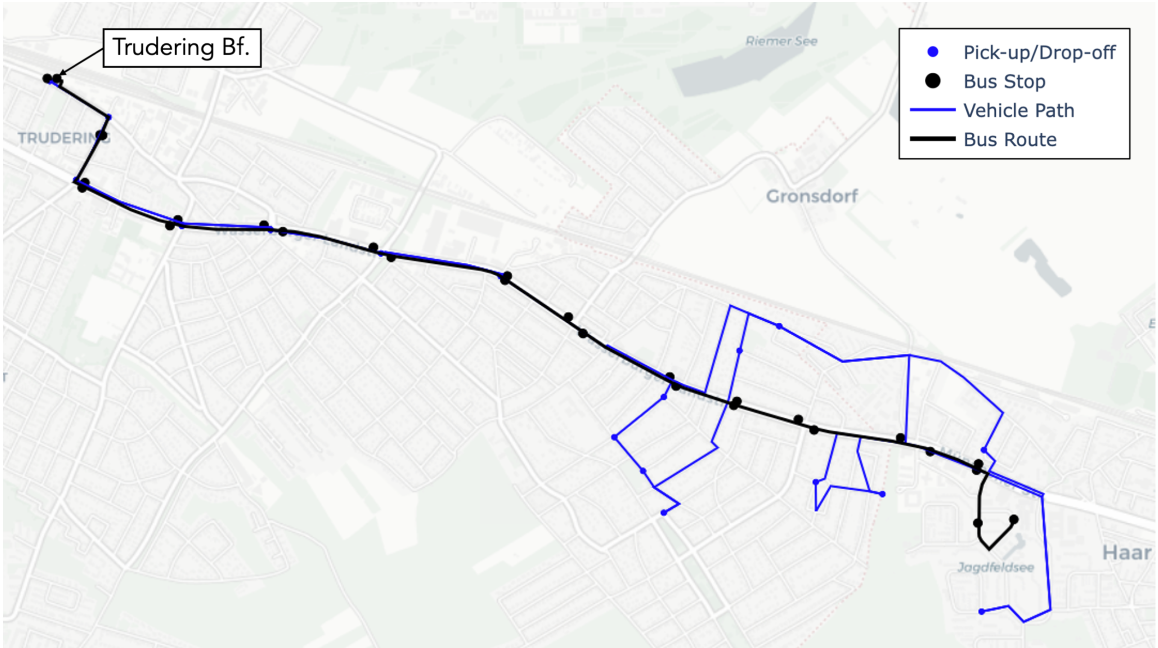

Figure 2: Munich bus route 193 and a simulated example of semi-on-demand hybrid route

distribution (in dashes). While walking times decrease, signifying better service accessibility, waiting times increase more due to the effects of detours on headway variance. Additionally, riding times decrease mildly, as contained by the limited number of satisfied requests.
In comparison with the theoretical values, the simulated walking time is similar with an initial small discrepancy likely due to the non-uniform demand distribution. The waiting time is around the theoretical level for the first 2km of the flexible portion, after which it shoots up due to the effects of increased headway variance. Lastly, the riding time fluctuates around the same level as opposed to the theoretical quadratic increase, probably reflecting the limit set by the detour factor.

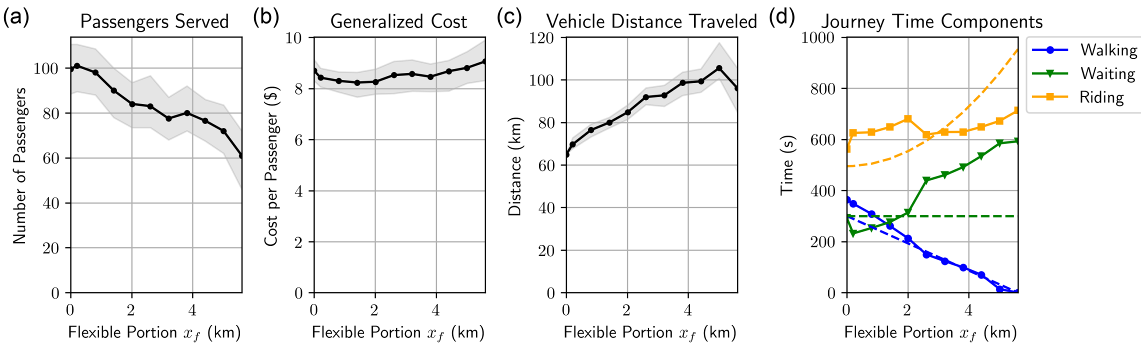

Figure 3: (a) Number of passengers served; (b) Average generalized cost per passenger; (c) Vehicle distance traveled; and (d) Journey time components under varying flexible route portions

We also analyzed the service performance with other headways as shown in Figure 4. Figure 4(a) indicates that the number of passengers served drops with longer flexible routes for longer headways, as each trip consists of more detours. Since the number of passengers served may be a hard constraint for service guarantees, cases that serve less than 95% of passengers are shown in dotted lines.
In Figure 4(b), it emerges that smaller headways favor longer flexible routes and reduce the generalized costs. Figure 4(c) and (d) show the fleet size required and average vehicle occupancy calculated by distance. In Figure 4(e), a sharp increase in operating costs is observed with smaller headways. For example, the operating costs associated with a 4-minute headway are around twice those of a 10-minute headway. This discrepancy underscores the operator's challenge in balancing the cost implications of enhancing service quality against the perceived value of time from the

passenger's perspective.
The optimal configuration, as corroborated by Ng, Dandl, et al. (2024), appears to be a lower headway combined with more vehicles and a more flexible route. This arrangement serves most passengers and minimizes the generalized costs per passenger (e.g., by 22% from \$8.4 of the fixed route to \$6.2 of the 5-km flexible route at 4-min headway), striking a balance between service quality and operational efficiency. However, an operating cost constraint would favor a smaller portion of flexible routes under a higher headway.

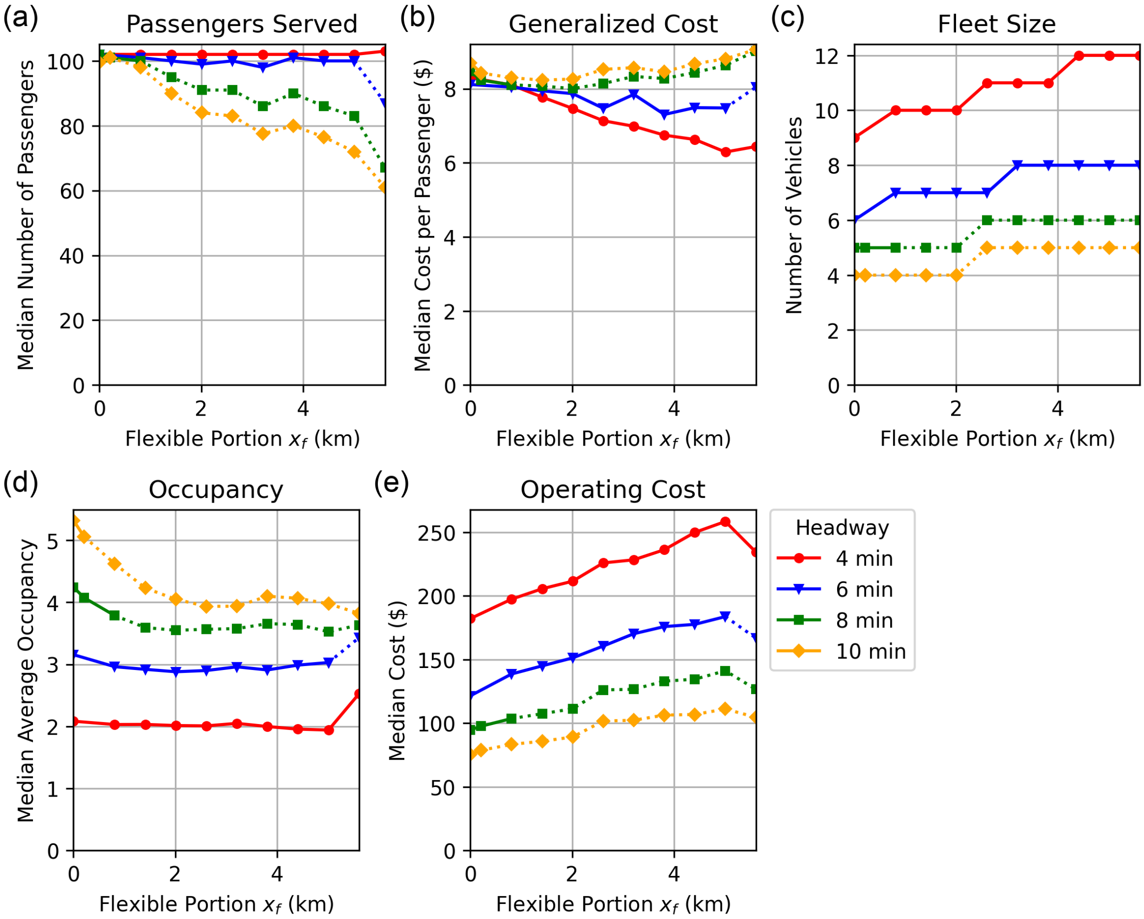

Figure 4: (a) Median number of passengers served; (b) Median generalized cost per passenger; (c) Fleet size; (d) Median average occupancy by distance; and (e) Median operating cost under varying flexible route portions and different headways

4 Conclusions

This study explored semi-on-demand hybrid route feeder services, validating their performance with real-world data and offering insights into operational strategies. Despite its proof-of-concept analysis, certain limitations could be addressed in future research:

1. Future studies should extend the analysis to a wider variety of routes with different characteristics, similar to the approach taken by Volakakis et al. (2023).
2. Some scenarios, particularly at high headways, do not serve all passengers, indicating the need for considering alternative modes such as bicycles, walking, or ride-pooling.
3. Reduced access costs and enhanced service quality would likely attract additional passengers. This favors longer fixed routes or smaller headway service-wise and also strengthens the economy of scale of transit. The demand elasticity should be evaluated.
4. The constant detour factor assumed in the simulation could be optimized to balance riding time and vehicle requirements.

5. Advanced fleet management strategies, such as zonal express services or parallel zone operations, could be explored to enhance service coverage and efficiency.

In conclusion, this study extends previous discussions of semi-on-demand hybrid route services with a simulation of a real-world bus route. Further research on its implementation strategy and benefits will advance our knowledge and application of hybrid route systems in public transportation.

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Appendix

Table 1: Results for base case

Flexible portion x_f (km)		0.0	0.2	0.8	1.4	2.0	2.6	3.2	3.8	4.4	5.0	5.6
Fleet size s		4	4	4	4	4	5	5	5	5	5	5
Headway h (min)		10	10	10	10	10	10	10	10	10	10	10
Number of requests	Mean	103.6	103.6	103.6	103.6	103.6	103.6	103.6	103.6	103.6	103.6	103.6
	SD	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2	5.2
	Min	88.0	88.0	88.0	88.0	88.0	88.0	88.0	88.0	88.0	88.0	88.0
	Max	118.0	118.0	118.0	118.0	118.0	118.0	118.0	118.0	118.0	118.0	118.0
	Median	104.0	104.0	104.0	104.0	104.0	104.0	104.0	104.0	104.0	104.0	104.0
Number of requests satisfied N^R	Mean	99.9	101.2	97.9	90.0	83.7	83.0	77.7	80.5	76.8	72.7	60.2
	SD	5.6	5.2	5.2	5.8	5.7	6.1	6.0	5.6	5.6	5.7	7.1
	Min	86.0	87.0	84.0	73.0	68.0	61.0	60.0	65.0	63.0	57.0	44.0
	Max	115.0	115.0	112.0	108.0	99.0	101.0	100.0	95.0	95.0	87.0	77.0
	Median	99.5	101.0	98.0	90.0	84.0	83.0	77.5	80.0	76.5	72.0	61.0
Average riding time $\overline{t_i^R}$ (s)	Mean	563	625	631	649	682	621	627	628	646	673	717
	SD	15.8	15.8	18.6	19.3	24.5	23.3	21.2	25.0	28.5	25.5	31.7
	Min	534	583	587	605	618	556	569	547	586	605	651
	Max	601	668	699	704	753	693	673	686	712	733	830
	Median	562	625	628	648	680	619	629	629	649	672	713
Average waiting time $\overline{t_i^W}$ (s)	Mean	295	233	252	277	312	442	464	490	529	588	589
	SD	18.3	13.1	17.0	20.8	29.6	33.7	35.8	33.5	35.2	32.6	43.4
	Min	241	203	214	232	246	366	399	410	421	510	476
	Max	354	266	300	323	416	539	560	576	599	661	721
	Median	293	232	253	276	314	439	460	491	535	585	592
Average walking time $\overline{t_i^A}$ (s)	Mean	365	348	308	260	210	151	126	100	67	15	1
	SD	16.8	17.1	18.2	19.6	17.8	17.2	18.7	14.4	13.7	6.9	1.8
	Min	316	305	263	214	170	105	84	61	33	0	0
	Max	398	392	343	307	258	192	173	135	107	32	9
	Median	364	348	308	261	213	149	123	99	70	14	0
Average user cost $\overline{c_i^U}$ (\$)	Mean	7.95	7.66	7.45	7.26	7.20	7.26	7.22	7.16	7.21	7.26	7.34

Table 1: Results for base case

Flexible portion x_f (km)		0.0	0.2	0.8	1.4	2.0	2.6	3.2	3.8	4.4	5.0	5.6
	SD	0.22	0.19	0.21	0.22	0.24	0.27	0.28	0.26	0.27	0.25	0.34
	Min	7.25	7.22	6.94	6.66	6.56	6.54	6.60	6.63	6.24	6.77	6.54
	Max	8.55	8.19	8.03	7.83	7.83	7.89	7.95	7.88	7.87	7.73	8.21
	Median	7.95	7.65	7.46	7.28	7.19	7.24	7.24	7.15	7.25	7.26	7.34
Vehicle distance $\overline{d_v}$ (m)	Mean	64957	69838	76288	79941	84628	92025	92678	98382	99558	106462	95977
	SD	90	1474	1582	1404	1802	2339	2704	2845	3083	4271	5865
	Min	64936	65870	72509	76899	80292	87841	83635	90196	93145	97667	81494
	Max	65388	74440	80547	83788	89702	97918	99020	104853	107670	119022	107348
	Median	64936	69675	76401	79928	84749	91926	92710	98588	99299	105513	96048
Vehicle occupancy	Mean	5.29	5.07	4.60	4.23	4.06	4.00	3.96	4.10	4.06	3.96	3.87
	SD	0.30	0.22	0.23	0.30	0.28	0.29	0.31	0.29	0.31	0.33	0.38
	Min	4.58	4.42	3.99	3.58	3.56	3.46	3.32	3.57	3.38	3.20	2.98
	Max	6.10	5.64	5.16	5.06	5.01	5.08	5.26	4.81	5.15	4.87	4.95
	Median	5.32	5.06	4.62	4.23	4.05	3.94	3.94	4.10	4.06	3.98	3.82
Vehicle cost $\overline{c_v^O}$ ($)	Mean	75.43	78.81	83.29	85.82	89.07	101.80	102.25	106.21	107.02	111.81	104.54
	SD	0.06	1.02	1.10	0.97	1.25	1.62	1.88	1.97	2.14	2.96	4.07
	Min	75.41	76.06	80.67	83.71	86.07	98.89	95.98	100.53	102.57	105.71	94.49
	Max	75.73	82.01	86.24	88.49	92.60	105.89	106.65	110.70	112.65	120.53	112.43
	Median	75.41	78.70	83.37	85.81	89.16	101.73	102.27	106.35	106.84	111.15	104.59
Total generalized cost c^G ($)	Mean	869.6	853.9	812.2	739.3	691.8	704.4	663.1	682.4	660.2	639.2	545.6
	SD	42.6	42.7	42.5	42.9	43.4	44.5	44.6	40.7	40.4	38.4	50.7
	Min	766.5	747.3	709.9	601.1	589.1	533.8	519.9	551.2	550.1	535.9	401.3
	Max	970.3	957.1	908.1	864.1	793.8	808.6	780.1	788.2	747.4	729.1	692.5
	Median	870.1	854.5	810.9	737.6	694.1	701.8	658.9	681.0	657.0	634.0	544.2
Generalized cost per passenger ($)	Mean	8.71	8.44	8.30	8.22	8.27	8.50	8.54	8.49	8.61	8.81	9.10
	SD	0.23	0.20	0.22	0.24	0.26	0.31	0.32	0.30	0.31	0.32	0.43
	Min	8.01	8.02	7.75	7.61	7.67	7.69	7.72	7.78	7.55	8.18	8.20
	Max	9.38	9.03	8.97	8.90	9.04	9.18	9.32	9.26	9.32	9.53	10.24
	Median	8.71	8.42	8.30	8.23	8.26	8.53	8.57	8.46	8.68	8.81	9.06