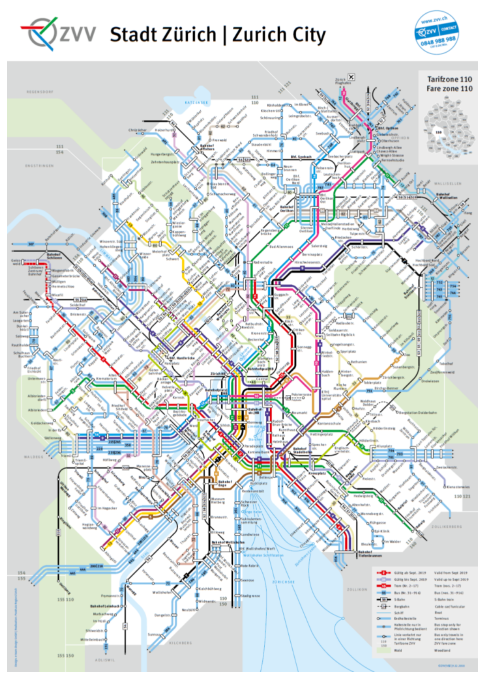
SEMESTER PROJECT

On-demand Service Integration and Coordination with Bus Schedule Operation



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1 Introduction

Many bus networks experience delays and long waiting times and bus bunching due to congestion, especially during rush hours. Fixed routes and schedules of bus services do not allow any flexibility in routing and adaptation to dynamic conditions. Once the roads are congested, the buses start accumulating delays. These inefficiencies not only inconvenience passengers but also hinder the overall reliability and appeal of public transportation.
This project focuses on the implementation of a microtransit service to assist and complement the existing bus network. Different KPI need to be considered to analyze the effects. Challenges include the right implementation and coordination. To set the scope of the project, the following two research questions were defined:

1. Can complementary flexible schedule microtransit service assist in improving service quality and performance of fix schedule buses?

2. How can proper coordination between the two services be ensured?

The remainder of this work is organized as follows. In Section 2, the existing literature related to on-demand microtransit services, ride sharing, and matching algorithms is presented. In Section 3, the Zurich bus network, which is the basis for this project, is described and analyzed. The simulation environment, consistent of a on-demand microtransit and bus simulation, is introduced in Section 4. This also includes the assumptions, parameters, and decision-making processes. Section 5 presents the results of different scenario. The results are then compared to different benchmark scenarios. To determine the impact of a higher microtransit capacity, additional scenarios with increased microtransit fleet sizes and vehicle capacities are presented in Section 6. Finally, the different insights and results are summed up in Section 7.

2 Literature Review

2.1 Dynamic Shared-Taxi Dispatch Algorithm with Hybrid Simulated Annealing by Jaeyoung Jung, R. Jayakrishnan, and Ji Young Park

Traditional taxi dispatch systems are often inefficient. Especially during peak hours, taxi availability is limited and inefficient use results in congestion. To address these problems, this study [3] proposes three algorithms in an effort to try to minimize passenger wait and detour times as well as maximize operational efficiency.
The Nearest Vehicle Dispatch (NVD) simply assigns the request to the nearest vehicle. The Insertion Heuristics (IS) iterates through all vehicles and finds the best match by minimizing the incremental cost. Hybrid Simulated Annealing (HSA) is a combination of overall system efficiency and optimizing individual schedules to reduce passenger's wait and detour times as well as overall cost.
To compare the different algorithms, the simulation was conducted with 600 vehicles in Seoul with varying demand rates and two different operation modes: one with ride sharing and one without. The KPI included passenger travel time, i.e. waiting and in-vehicle time, system profit, vehicle utilization, and computational efficiency.
The study found that HSA results in significant improvements in both passenger travel time and system profit, especially for higher demands. Shared taxi use further increased service efficiency while maintaining acceptable detour times. However, computational efforts increased, but were considered manageable.

2.2 On-demand high-capacity ride sharing via dynamic trip-vehicle assignment by Javier Alonso-Mora, Samitha Samaranayake, Alex Wallar, Emilio Frazzoli, and Daniela Rus

In this paper [4] a reactive anytime optimal mathematical model is developed for on-demand high-capacity ride-sharing trip assignment. The model first computes a pairwise request-vehicle shareability graph, then a graph of feasible trips with then vehicles that can serve them and after assigns trips to vehicles following an ILP initialized with greedy assignment (Lin-Kernighan,tabu search and simulated annealing can be used). The constraints are maximum waiting times, maximum additional delays and capacity. The objective minimizes total delay and adds a penalty for unassigned requests. Finally, the rebalancing of the remaining vehicles is

done. Parameters such as fleet size, capacity (up to 10 passengers), waiting time, travel delay, operational costs are taken into account.
The New York city dataset of taxicab is used for the simulation with a shared fleet. The results show that if 15% of the fleet is of capacity 10 or 22.5 of capacity 4, 98% of the demand is served with a mean waiting time of 2.8 min and a mean trio delay of 3.5 min. It is also observed that higher capacity increases occupancy, service rate and reduces mean distance by the vehicles and waiting time. Rebalancing increases service rate by 20%. Finally, this model can also apply to fleets of autonomous vehicles and is robust.

2.3 Exploring first-mile on-demand transit solutions for North American suburbia: A case study of Markham, Canada by Johanna Bürstlein, David Lopez, and Bilal Farooq

This study [5] addresses the under-utilization of public transport in the Toronto suburb Markham. As public transport is limited, most residents rely on cars to get to the train station, causing high levels of greenhouse gases and congestion. To solve this, this article discusses the impact of adding a shared on-demand solution to replace car rides for the first part of the commute.
The simulation assumes morning peak hours with microtransit vehicle capacities of 4 and 7 as well as different fleet sizes and detour limits. In addition, it is assumed that passengers get picked up at fixed stops and all first-mile trips are replaced by the shared on-demand service. Multiple KPIs were used to analyze the impact, such as waiting time, in-vehicle travel time, satisfaction, cost, and environmental impact.
The study found that vans, i.e. vehicles with capacity of 7, with a fleet size of 75% of the optimal are the most efficient solution. Average waiting and in-vehicle times were 3 and 10 minutes, respectively. Costs were able to be reduced by 7% compared to private cars. This value could be increased if parking fees at the train station were increased or parking opportunities removed. Lastly, greenhouse gas emissions were can be reduced by 30% compared to private car use.
Several policies were proposed to implement this service: Subsidies can be used to make the service more attractive, e.g. by eliminating booking fees. A smooth integration with train services is necessary to complement existing commuter services. And a dense network of pick-up and drop-off stops reduce walking distances and increase accessibility.

2.4 Integrating On-demand Ride-sharing with Mass Transit at-Scale by Danushka Edirimanna, Hins, Hu, Samtha Samaranayake

This paper [2] introduces the Transit-Integrated Request-Trip-Vehicle (TI-RTV) model, which integrates ride-sharing with mass transit to optimize urban transportation. It defines a trip as a collection of travel segments, including first-mile, last-mile, and full ride-sharing routes. The model constructs a TI-RTV graph with strict compatibility constraints. It uses two bipartite graphs to match requests to trips and trips to vehicles, optimizing cost and feasibility while considering Quality of Service constraints such as waiting time and travel-time delay. The optimization is formulated as an Integer Linear Program (ILP) to assign trips to vehicles and requests to travel options and is solved every 100 aggregated requests (approximately every 30 sec.). The objective minimizes vehicle miles travelled and adds penalties for unserved requests. The model also incorporates dummy vehicles for unserved segments and accounts for bus capacity conflicts. For the non-multi-modal trips the framework can easily adapt to bus-to-bus transfers.
The model is applied on 5 cities in the US using real-world data form the LEHD Origin-Destination Employment Statistics (LODES) and OpenStreetMap. Different scenarios are investigated with distinct capacities, fleet sizes and different service systems (the transit-integrated ride-sharing, ride-sharing and only the multi-modal option).
The results show that the transit-integrated ride-sharing system can decrease the total vehicle miles traveled by the ride-sharing vehicle fleet by up to 20% while increasing the service rate by up to 12%, particularly in cities with robust transit systems like Boston and Chicago. Multi-modal trips dominate at smaller fleet sizes, with on-demand only trips increasing as fleets grow. The system efficiently serves up to 43% of demand with small fleets of 10 vehicles per 1000 requests. These results highlight the model's potential to enhance transportation efficiency and sustainability.

2.5 Comparison

These four studies explore different innovative approaches to public transport optimization in urban areas through ride-sharing algorithms. Each study analyzes a different approach, like taxi dispatch [3], first-mile transit solutions [5], or multi-modal integration[2]. However, all papers aim to reduce waiting time and travel costs as well as to optimize serviceability and system efficiency. The studies employ advanced computational techniques like Hybrid Simulated Annealing [3], Integer Linear Programming[2], and dynamic trip-vehicle assignment models[4], consistently demonstrating that intelligent ride-sharing systems can significantly enhance urban mobility. The different approaches show that significant reductions in vehicle miles traveled, greenhouse gases, waiting and travel times can be achieved. However, the existing literature needs further research on the economic aspects, long-term impact, consumer behavior, and integration with existing transportation systems. This project focuses on the latter. The goal is not to replace existing services but to complement them where service levels are low.

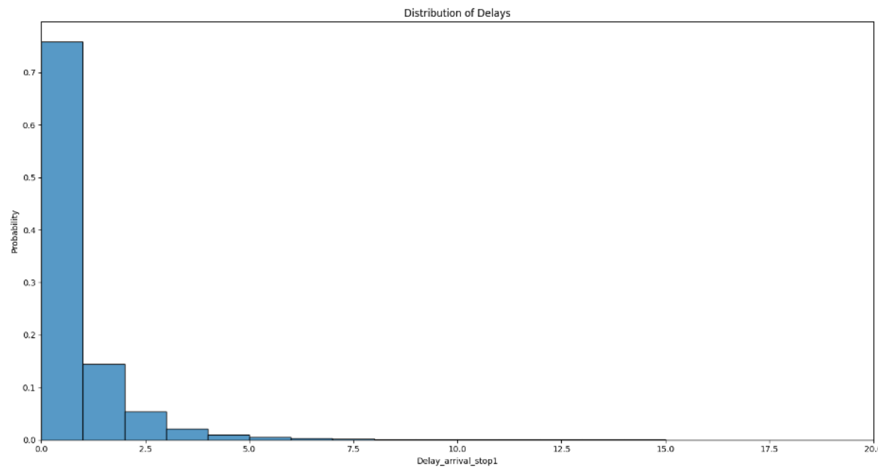


Figure 1: Average Delay distribution for the entire system on a week

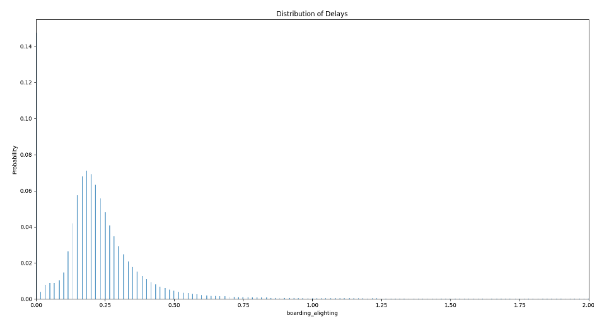


Figure 2: Average boarding alighting time distribution for the entire system on a week

3 Zurich Bus Network

This section introduces the reference network that was used for the simulations. While a simple test network can be used to check if the simulation is running properly, it cannot generate realistic and reliable results. By using a real bus network with historic data, human behavior and patterns will be accounted for in the data, and the impacts of the integration of on-demand microtransit services can be determined more reliably.
For this project, the Zurich bus network was used to simulate the buses and on-demand micro-transit. To start off, the network was analyzed by identifying weak points and bottlenecks. Then, the most critical lines were chosen and simulated. And lastly, the on-demand micro-transit simulation was implemented. Different scenarios and strategies were tested to determine the effectiveness of adding on-demand micro-transit services to supplement the bus services.

3.1 Analysis

The city of Zurich provides thorough weekly data of their bus services [1]. These data include the stop id, the bus line number, the direction and the actual and expected arrival and departure times. For the analysis, data from 3 different weeks were separately analyzed. The weeks were: 14/05/2023-20/05/2023, 18/06/2023-24/06/2023 and 09/07/2023-15/07/2023. Different delay metrics were computed for each week in order to spot the most problematic lines. The delay was considered as the difference between the expected arrival time and the actual arrival time at each stop.
Initially, to provide an overall understanding, aggregate measures were plotted. The figures (figures 1 and 2) show the average distribution of delays and the average distribution boarding alighting times for a week.
It can be seen that boarding and alighting generally take less than 0.5 minutes, and buses arrive less than 1 minute late in 75% of the cases and less than 5 minutes late in most cases.

Secondly, the delays were analyzed more thoroughly. The first metric calculated was the number of times a

	line	delay_count
0	31	503
1	75	215
2	302	212
3	11	71
4	304	66
5	7	64
6	80	63
7	301	59
8	4	41
9	309	37

	line	delay_count
0	32	308
1	75	182
2	165	178
3	31	176
4	4	145
5	80	137
6	912	79
7	83	78
8	13	76
9	302	68

	line	delay_count
0	31	1476
1	32	392
2	83	286
3	33	274
4	11	195
5	2	135
6	4	130
7	14	128
8	13	120
9	17	120

Figure 3: Delay count: number of times a bus line was more then 10 minutes late to a stop over the course of a week (top 10 for three distinct weeks)

	line	Delay_arrival_stop1
0	91	1.220837
1	701	0.972681
2	31	0.916416
3	32	0.855389
4	75	0.799951

	line	Delay_arrival_stop1
0	91	1.416103
1	31	1.339463
2	32	1.200565
3	165	1.097615
4	910	1.063704

Figure 4: Delay arrival: average delay in minutes for a line in a week (top 5 for two distinct weeks)

bus line was more than 10 minutes late to a stop over the course of a week. The results for the 3 weeks are illustrated in the figure 3. Lines like 31 and 32 and 75 often appear in the lead.

The average delay per line over a week was computed and again we can observe some of the colored lines in the tables above, like 31 and 32 and even 75 are found again on the top (Figure 4). Line 91, although having the highest average delay for two distinct weeks, does not appear in the tables in figure 3 indicating that the high average delay was probably due to a specific high delay event that occurred and not due to recurring delays. Therefore, the line was not selected.

Other metrics that were computed were the maximum delay that occurred in a week and the number of bus bunching occurrences in a week. Figure 5 illustrates the maximum delays for one of the weeks and the corresponding bus line and direction next to it. Lines 31, 32 and even 33 not only are seen to have recurring delays but also very high ones sometimes.

Finally, the number of times bus bunching happened at a stop for every line over a week was computed. A bus bunching event was considered at a stop if the next bus in the same direction was arriving in less than 30 seconds from the previous one, both buses being on the same line. The count of bus bunching events is shown in figure 6. The same lines are on the lead for two distinct weeks.

3.2 Critical Bus Lines

After considering all these factors, the following bus lines were chosen as the most critical for this project: 31, 32, 33, 46, 75, 80. Lines 31, 32, and 33 are lines that mostly pass through the city center and were found problematic in terms of recurring and high delays and bus bunching. Lines 75 and 80 were both on the lead of bus bunching events and some repeated delays for a few weeks. Line 46 was also considered, as it was on the lead of bus bunching for both weeks. Additionally, these last 3 lines have more stops outside the city center towards the suburbs, so it was another factor that made us select these instead of other central problematic ones like 11, 2, 4. This allowed for a broad network that includes both 'center' stops and 'outskirt' stops. Figure 7 shows the relative position of the lines and their corresponding stops.

To verify our hypothesis that these lines were problematic, time-space diagrams were plotted for each of the

	line	direction	Delay_arrival_stop1
0	72	2	50
1	7	1	49
2	31	2	33
3	2	2	32
4	32	2	32
5	14	2	30
6	33	1	27
7	31	1	27
8	302	2	26
9	32	1	25

Figure 5: Delay arrival: maximum delays in minutes in a week (top 10)

	line	bunching_count
0	80	78
1	46	64
2	31	63
3	33	50
4	75	41
5	89	38
6	13	30
7	32	22
8	7	20
9	66	19

	line	bunching_count
0	31	182
1	33	104
2	32	91
3	46	81
4	80	58
5	83	44
6	89	40
7	76	39
8	66	22
9	8	17

Figure 6: Bunching count: number of times bus bunching happened at a stop for every line over a week (top 10 for two distinct weeks)

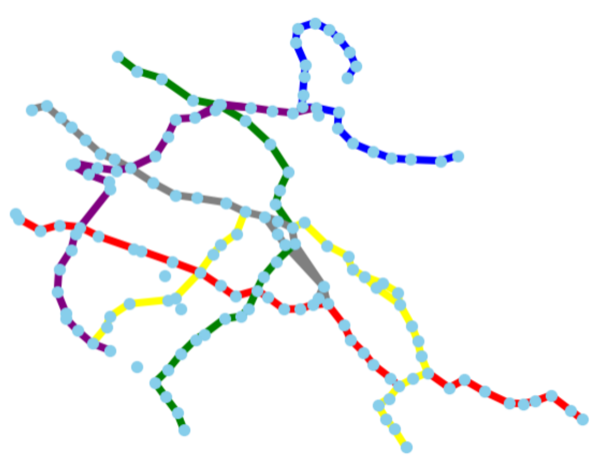
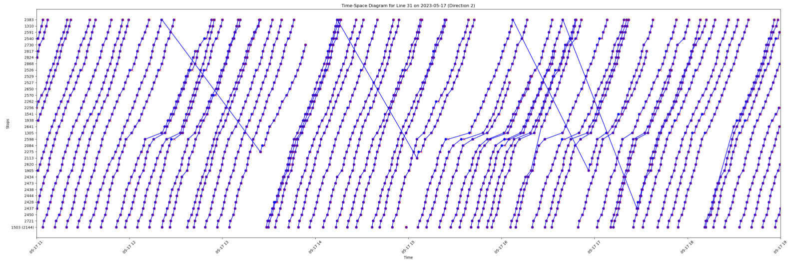


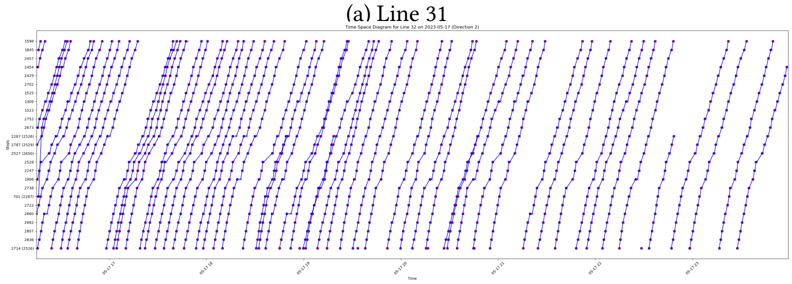
Figure 7: Graph containing the stops and edges of the critical lanes: lane 31 = red, 32 = green, 33 = yellow, 46 = gray, 75 = blue, 80 = purple

selected lines (Figure 8). The plots clearly show that there are bus bunching events and high delays in critical bottlenecks. Sometimes, buses followed unusual routes. It is assumed that buses may have been routed due to delays and roadblocks. However, these were not further analyzed or considered.

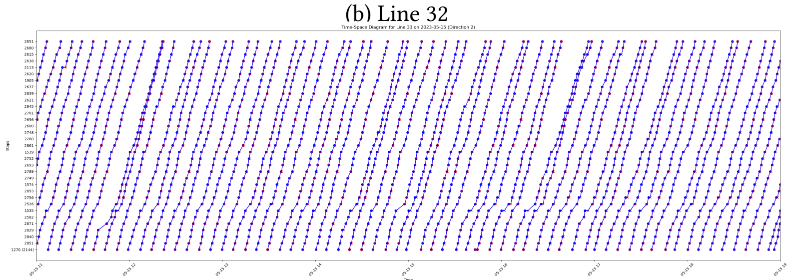
The stops where the larger and repeated delays happened are illustrated in the figure 9a below in red. Most of them seem to be in the pink radius illustrated in the figure 9b. This radius corresponds to the center nodes. It can, therefore, be concluded that the largest delays mostly happen in the city center. Finally, the delay distributions of the most problematic stops by lane and by direction are illustrated in figure 10.



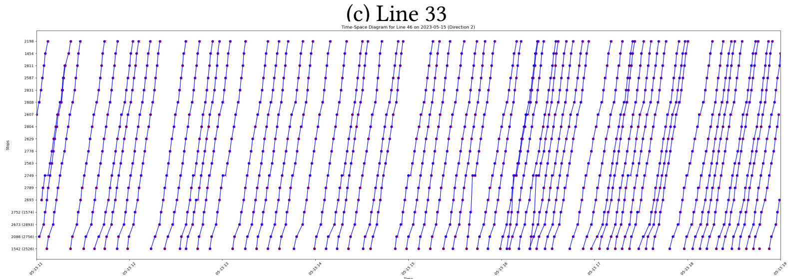
(a) Line 31



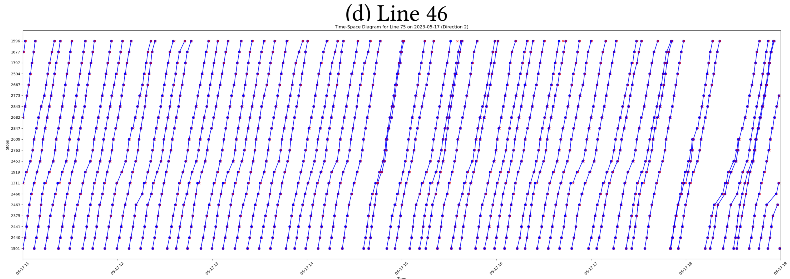
(b) Line 32



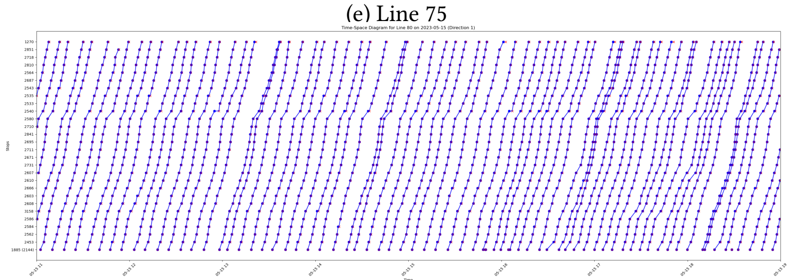
(c) Line 33



(d) Line 46

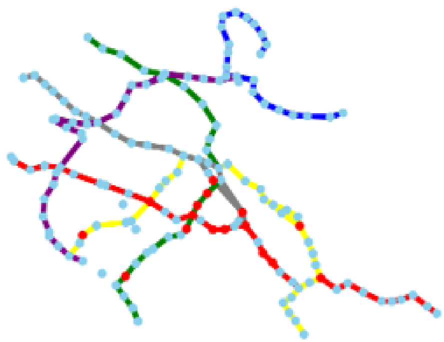


(e) Line 75

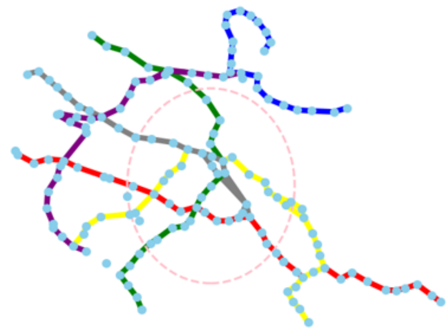


(f) Line 80

Figure 8: Time-space diagrams of the selected lines.



(a) Network graph with most problematic nodes in red



(b) Network graph with pink radius illustrating the 'center' nodes

Figure 9: Zurich Network Graph

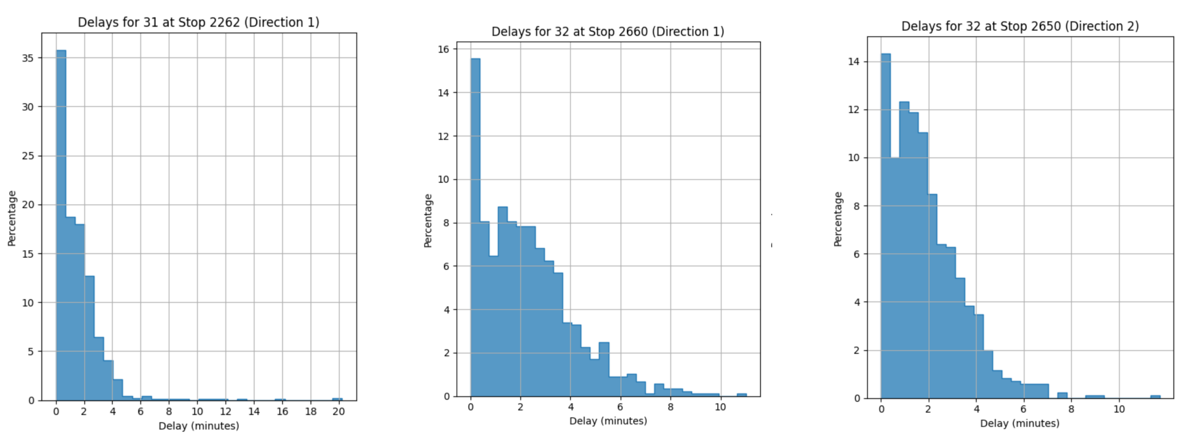


Figure 10: Delay distributions for the stops with highest delays by bus line and direction

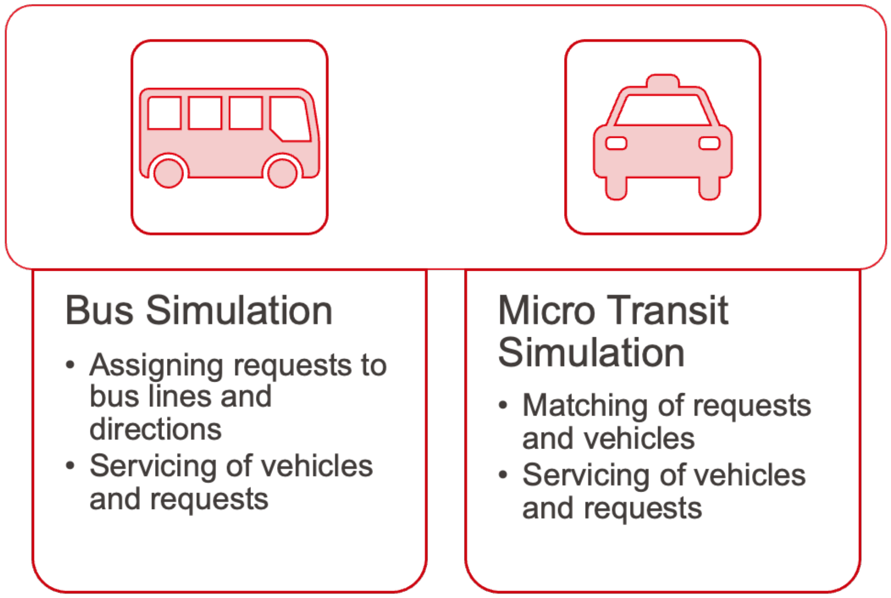


Figure 11: Overview of the Simulation Environment

4 Simulation Environment

The simulation environment of this study contains two separate simulations. The first simulates bus services. It assigns every request to possible bus lines and directions that can be taken to reach the destination.
The bus environment then services both buses and requests. When a bus arrives at a station, bus attributes get updates and waiting passengers are picked up if there is capacity and the bus line and direction is among the possible combinations.
The microtransit simulation matches the passengers to microtransit vehicles once the requests come in. It also services vehicles. Similarly to the bus simulation, vehicle attributes get updated, and assigned passengers get picked up or dropped off when a vehicle arrives at a station.
In the main simulation, there are three events that occur and require an intervention:

1. Microtransit vehicle arrival at a station
2. Bus arrival at a station
3. New request

Interventions are executed according to the Event Intervention Scheme in Figure 12.

1. If a microtransit vehicle arrives at a station, waiting passengers get picked up, arriving passengers dropped up, and the vehicle attributes updates. Assignment of the passengers occurs when a new request comes in.
2. When a bus arrives at a station, the vehicle attributes are updated and arriving passengers dropped off. If there are waiting passengers that can use the bus to reach their destination, those passengers are picked up. If the bus is at capacity, passengers that cannot be served will be re-evaluated, that is, the two modes are compared again and the request is assigned to microtransit if it is more efficient. Otherwise, the passengers waits for the next bus.
3. When a request comes in, the modes are compared and the request is assigned to the more efficient one (cf. section 4.3).
   (a) If the request is assigned to the bus service, possible bus lines and directions are identified.
   (b) IF the request is assigned to the microtransit service, the request is assigned to the best vehicle using a greedy algorithm. If no vehicle can be assigned to the passenger due to constraint violations, the request is reassigned to the bus service (cf. (a)).

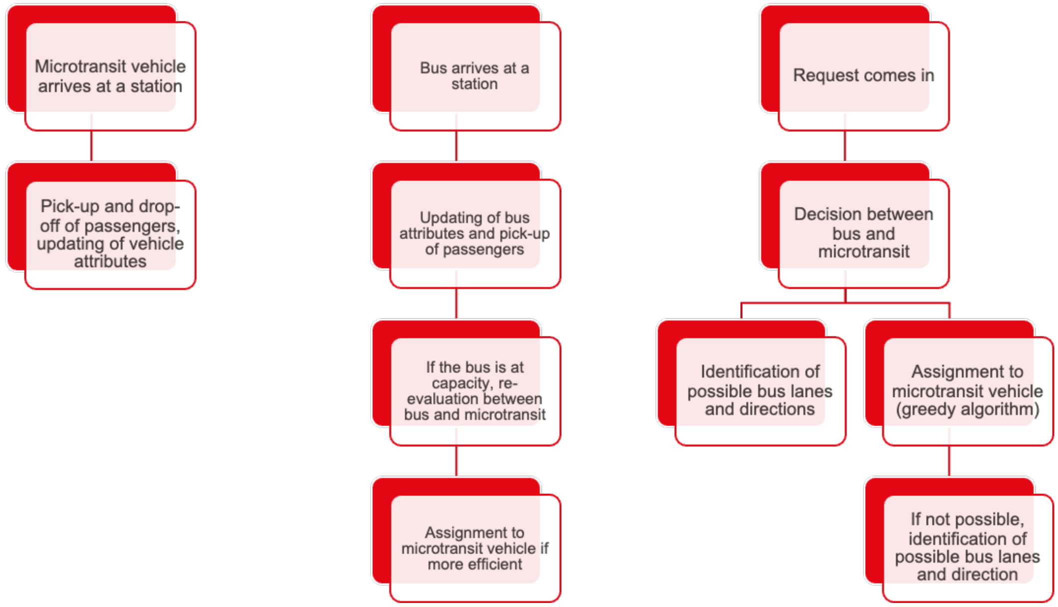


Figure 12: Event Intervention Scheme

The following chapter states the assumptions that were taken, looks at the two simulations more closely, and discusses the decision making process determining which simulation a request is assigned to.

4.1 Assumptions

The following assumptions are made for this project:

1. All requests can be served by one single bus trip. Requests are generated as follows: The origin is randomly chosen among all stops. The destination is a random stop than can be reached by any bus serving said stop.

2. Passengers are waiting until they are served. They do not leave after a certain time.

4.2 Inputs

The simulation environment is constructed as generically as possible. This requires numerous inputs but allows to adjust the simulation to various scenarios. The required inputs are described in table 1. All inputs can be adjusted to the simulation conditions.
The simulation inputs can be determined in various ways. The lanes were taken from the Zurich network analysis. As a result, the nodes_IDs and fleet size of the bus network were taken from real-world data. Inputs like vehicle_ID_to_lane_IDS and previous_bus are indirectly connected to real-world data. Eventually, there are a few inputs that need to be decided on or tuned to ensure a proper running of the simulation.

4.2.1 Parameter Tuning

The parameters are distinguished into three different types: universal parameters that apply to the entire simulation, bus parameters that apply to the bus simulation only, and microtransit parameters that apply to the microtransit simulation only.
Universal Parameters
There are only three universal parameters, i.e., parameters, used for the entire simulation environment (table 2).
Bus Parameters
The parameters for the bus simulation only include the specifications of the vehicles, that is, the size and capacity of the fleet (table 3).
Microtransit Parameters

Input	Type	Description
	Inputs for the whole simulation environment	
lanes	Dictionary	Dictionary containing the IDs for every stop for each direction of each bus line
nodes_IDs	List	List containing the IDs of all stops in the network
interstation_time	Dataframe	Two-dimensional matrix containing the time in hours between two stops calculated through linear distances and scaling them with real bus data
demand_rate	Integer	Hourly demand rate in the whole network
duration_of_simulation	Float	Time over which the simulation is run, including the start-up phase
threshold	Float	Threshold to vary change the decision likelihood for either mode
	Inputs for the bus simulation	
fleet_size	Integer	Number of buses in the whole network, calculated from real-world data
vehicle_capacity	Integer	Capacity of a bus, assumed to be 30 as a trade-off of computational effort and real-world capacity
vehicle_ID_to_lane_ID	Dictionary	Dictionary containing all the vehicle IDs and their assigned bus line
previous_bus	List	List containing the previous bus for every bus
	Inputs for the microtransit simulation	
maximum_waiting_time	Float	Maximum waiting time constraint in hours for the assignment of microtransit
maximum_detour_time	Float	Maximum detour time constraint in hours for the assignment of microtransit
cabacity	Integer	Capacity of a microtransit vehicle
fleet_size_cab	Integer	Number of microtransit vehicles in the network
optimization_objective	"wait", "detour", "wait+detour"	Optimization function used for the assignment of microtransit
	Scenario-specific inputs	
give_up	Float	Time after which the passenger decides to leave without being served
re_evaluation	TRUE, FALSE	Boolean deciding whether a request is re-evaluated (between the two modes) when the request cannot be served by bus due to capacity constraints
max_re_evaluations	Integer	Number of times the request can be re-evaluated when it cannot be served by a bus running at capacity
scenario	"normal", "morning", "evening"	Input deciding on the demand distributions
peak_increase	Float	Factor by which demand is increased during peak hours
center_nodes	List	List containing all the node_IDs of the center noes
outskirt_nodes	List	List containing all the node_IDs of the outskirt, i.e. not center, nodes
peak_start	Float	Time of simulation at which the demand is increased
peak_end	Float	Time of simulation when the demand increase ends
std_bus	Float	Standard deviation of the bus delay when the network is congested
mean_bus	Float	Average delay of the bus when the network is congested
mean_cab	Float	Average delay of microtransit vehicles when the network is congested
congested_nodes	List	List with the node_IDs of the congested nodes
congestion_start	Float	Time of simulation when congestion starts
congestion_end	Float	Time of simulation when congestion ends

Table 1: Inputs of the simulation

Parameter	Value	Reasoning
duration_of_simulation	4 (5)	A duration of 4 hours allows for the simulation to converge to a stable level where KPI can be calculated. The duration includes 1 hour for the start-up phase which is excluded from the KPI calculation. May be increased to 5 hours for certain scenarios.
threshold	0	Purposely worsening one mode has no positive effect on overall network performance.
demand_rate	5000	Demand rates which puts the network under stress. Higher demand leads to a collapse.

Table 2: Tuned parameters for the entire simulation environment

Parameter	Value	Reasoning
vehicle_capacity	30 (33)	Trade-off between computational effort and real-world bus capacities. This parameters may be increased for benchmark scenarios.
fleet_size	48 (52)	Correspond to the real-world data for the chosen bus lines. This parameter may be increased for benchmark scenarios.

Table 3: Tuned parameters for the bus simulation

Microtransit parameters describe the microtransit vehicles as well as optimization settings. The tuning and effect of the parameters on the network is described more in detail in section 4.4.2 (table 4).
In order to make the choices for some fixed microtransit parameters some comparisons of different fleet sizes were made and a higher fleet size improved the overall metrics. In the figure below the comparison of fleet sizes on the KPI of overall average waiting time of the system is illustrated.

4.3 Decision-Making

Two different decision-making strategies were used to assign requests to the bus or microtransit service. One compares the exact results of both directly while the other compares estimates of the arrival time.

4.3.1 Comparison

The first strategy calculates the expected arrival time for every request. For the bus simulation, the arrival time of the next bus is calculated and the given interstation time is added. For the microtransit simulation, however, the optimization algorithm has to be executed for every request using significant computational resources. To limit this, a threshold was introduced 15. If the next bus arrives below a certain threshold, the request would be assigned to the bus immediately, as the wait is assumed to be reasonable.

Parameter	Value	Reasoning
maximum_waiting_time	15/60	15 minutes is assumed to be reasonable and allows network improvements.
maximum_detour_time	20/60	20 minutes is assumed to be reasonable and allows network improvements.
optimization_objective	"wait+ detour"	Optimizing over both wait and detour times results in the largest improvement.
cab_fleet_size	30	The fleet size of the microtransit vehicles
cabacity	4	The microtransit vehicles are assumed to be cars. Results have also shown that microtransit becomes less effective with increasing vehicle capacity.

Table 4: Tuned parameters for the microtransit simulation

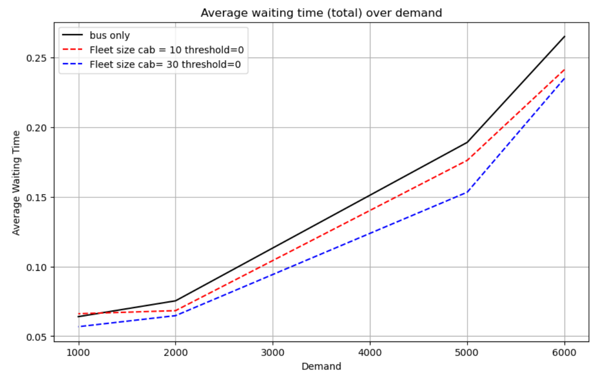


Figure 13: Comparison of fleet sizes on the KPI of overall average waiting time of the system

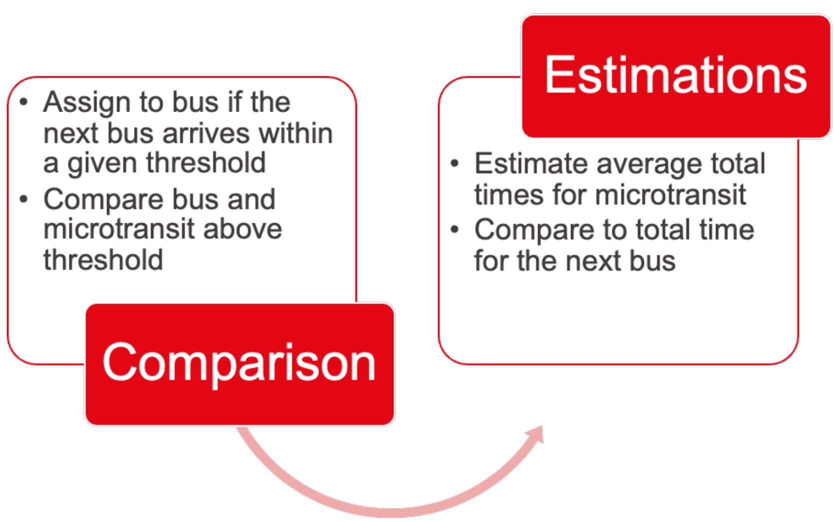


Figure 14: Different decision-making strategies

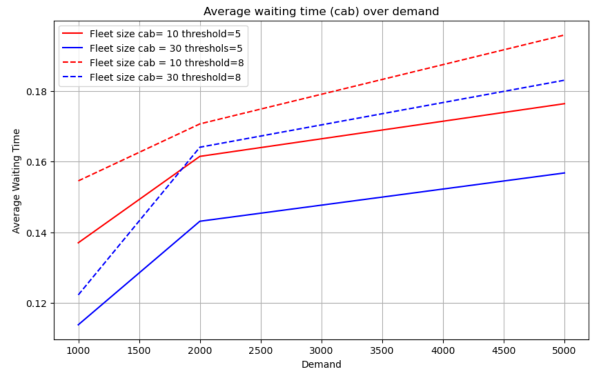


Figure 15: Comparison of different threshold values and microtransit fleet sizes, average waiting time in hours

While this saves computational resources, it makes the microtransit service worse as the minimum waiting time is at least the threshold. In addition, the computational efforts were still significant, making the simulation inefficient. To solve this problem, estimates were introduced.

4.3.2 Estimates

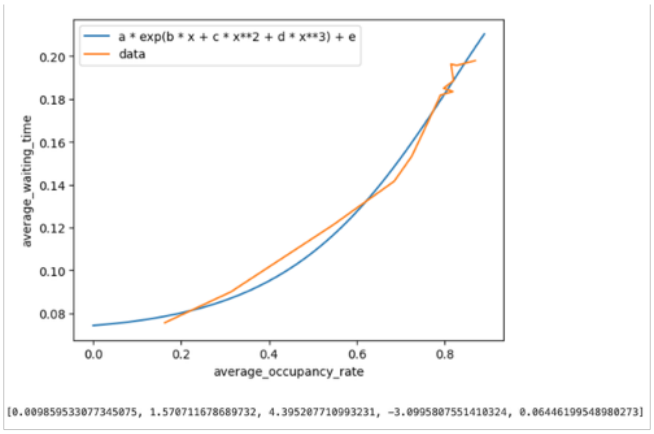
The second strategy relies on estimates for the microtransit simulation. The arrival time for buses can be easily calculated. The estimates take the average occupancy rate of all microtransit vehicles as input and calculates the estimates waiting and detour time based on an exponential fit. A threshold to add a constant to the estimate was introduced as well, but setting to 0 has to proven to be the best solution.
The estimates consists of the average waiting time and the average detour time divided by the average inter-station time. The waiting time is assumed to be constant as the distance to the next available microtransit vehicle does not depend on the trip length. On the other hand, the detour times is normalized by the interstation time, as detours are assumed to be proportional to the trip length. The curve fitting was done for both fleet sizes 10 and 30. However, fleet size equal to 10 did not show significant improvements to the network. Therefore, fleet size 30 was chosen for the continuation.

4.4 Microtransit Simulation

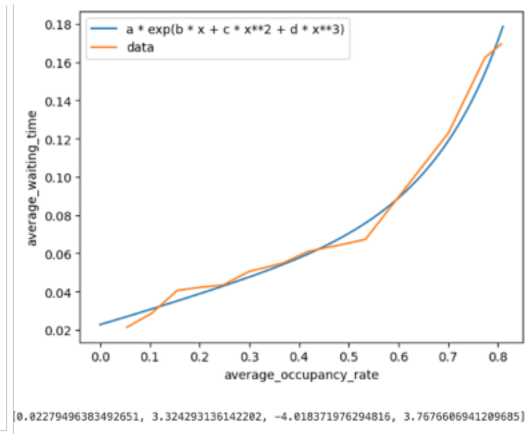
One component of main simulation is the on-demand microtransit simulation. A fully working python script was provided by Lynn Fayed and LUTS. It is run on a model network only containing 10 nodes to understand how it works and to analyze the impacts of varying certain parameters, i.e.:

- $demand\_rate$: The number of requests that are generated per hour. Every scenario was simulated with the following demand rates: 50, 100, 200, 500, 1000.
- $fleet\_size$: The number of microtransit vehicles operating on the network. Default value: 10
- $maximum\_waiting\_time$: The maximum waiting time that is allowed when assigning the requests to the vehicles. If the constraint cannot be met, the request will not be served. Default value: 10 minutes
- $maximum\_detour\_time$: The maximum detour time that is allowed when assigning the requests to the vehicles. If the constraint cannot be met, the request will not be served. Default value: 10 minutes
- $capacity$: The capacity is the number of passengers a vehicle can transport at a time. Default value: 10
- $objective\_function$: The objective function describes how the vehicle assignment should be optimized. "wait" reduces the total waiting time, "detour" the total detour time. The objective "wait+detour" combines the two function, i.e. the sum of the waiting and detour time. Default: "wait+detour".

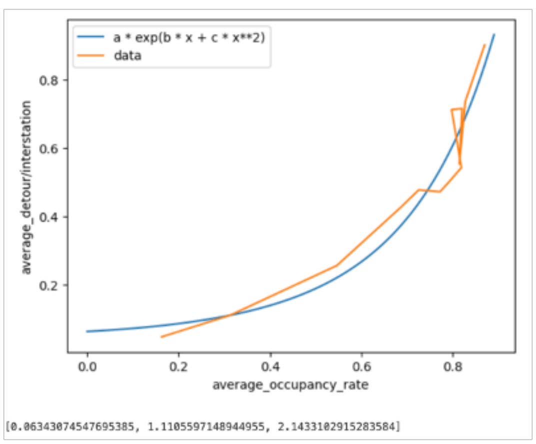
Instead of picking up and dropping off passengers at any location in the network, requests in this simulation can only be made from predefined stops closest to the origin and destination. This stops coincide with the bus stops in the bus and main simulations.



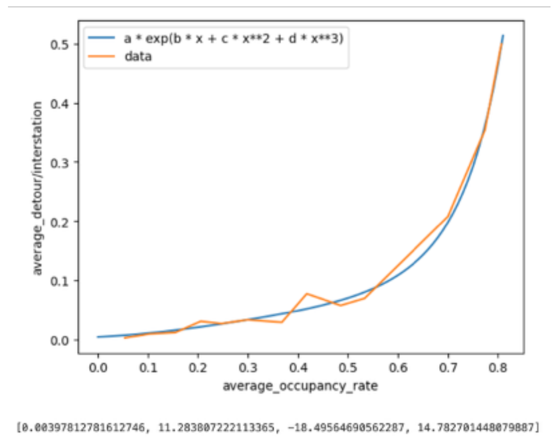
(a) Average waiting time over average occupancy rate for fleet size 10



(b) Average waiting time over average occupancy rate for fleet size 30



(c) Average detour time divided by average interstation time over average occupancy rate for fleet size 10



(d) Average detour time divided by average interstation time over average occupancy rate for fleet size 30

Figure 16: Exponential fits for decision-making between the two modes

4.4.1 Simulation

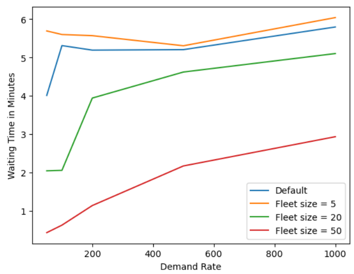
The given code first initializes the stations, interstation times, vehicles, and input variables. The input variabeles are the parameters described above.
Afterwards, the simulation starts. First, all requests are created in a list. The request time is uniformly distributed during the simulation duration, and the origin and destination are randomly chosen from the stops. Then, the simulation handles the first event or request and assigns it to the closest vehicle. Afterwards, one of two types of events can happen: A new request is made, or a vehicle arrives at a station.
Event: Request
If a new request is made, a greedy insertion heuristic iterates through all vehicles. First, it checks whether the origin and destination are already in the vehicles. If not, the greedy function runs through all possible insertions in the existing route. To check if a solution is feasible, the vehicle must not operate at capacity, and the maximum waiting and detour constraints cannot be violated. Finally, the feasible solution with the lowest cost, i.e. the lowest value of the objective function, is chosen.
Event: Vehicle Arrival
If a vehicle arrives at a station, the attributes of the vehicle are updated. This includes the current position, occupancy, and route. In addition, the actual arrival time of the arriving passengers is recorded.

4.4.2 Key Performance Indicators

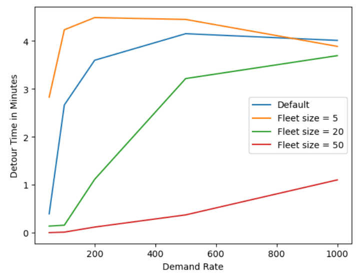
Four Key Performance Indicators were considered for this simulation:

- Average Waiting Time: The average waiting time of the requests, i.e. the time between the actual pickup time and the time the request was made.
- Average Detour Time: The average detour time of the requests, i.e. the difference of the travel time and the direct interstation time.
- Average Occupancy Rate: The average occupancy rate is a weighted average over time of the occupancy of the vehicles divided by their capacities.
- Acceptance Rate: The acceptance rate is the percentage of requests that were served.

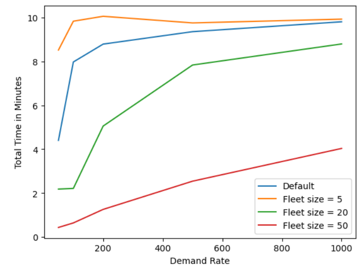
Overall, it can be said that average waiting and detour times, as well as occupancy rates decrease with higher fleet sizes, capacities, and higher constraints. The acceptance rate increases as expected. The results become more important with higher demand rates as the network is running under stress.
Varying fleet sizes
Figure 17 show that increasing fleet sizes reduce waiting, detour, and thus total times as well as average occupancies. This can be explained by the added capacity. The microtransit vehicles can serve more people at a time. This is as expected. As a result, service rates increase. The comparison over multiple demand rates shows that the waiting, detour, and total times have an upper bound for lower capacities, i.e. smaller fleets, due to constraint violations. Falling acceptance rates support this explanation.
Varying capacities
Effects for varying capacities are similar to varying fleet sizes, as both increase overall capacities.
Varying maximum waiting times
Increasing the maximum waiting time constraint increases the acceptance rate, as more passengers can be served. In turn, the average waiting and total time increase as a consequence. An equilibrium needs to be found to balance a reasonable waiting time and service levels.
Varying maximum detour times
Similar to the waiting constraint, increasing the maximum detour time constraint increases the acceptance rate, as more passengers can be served. In turn, the average detour and total time increase as a consequence. Again, a balance between a reasonable waiting time and service levels needs to be found.
Varying optimization objectives
Figure 21 shows that optimizing over both wait and detour is the best objective. It shows the highest service rate and the lowest total time. When optimizing only over either wait or detour, the other component increases resulting in longer total times.



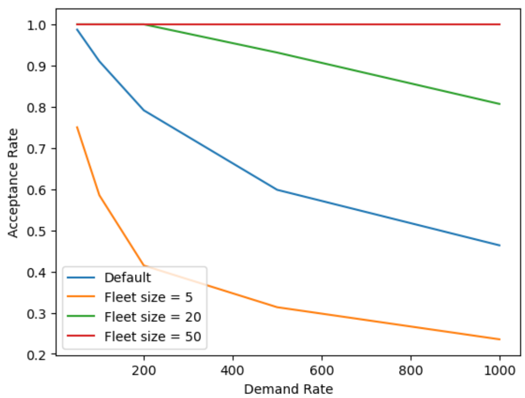
(a) Waiting Time over Demand Rate



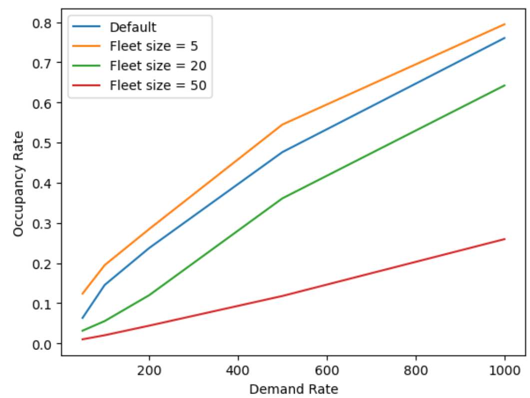
(b) Detour Time over Demand Rate



(c) Total Time over Demand Rate

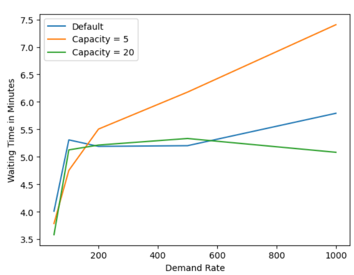


(d) Acceptance Rate over Demand Rate

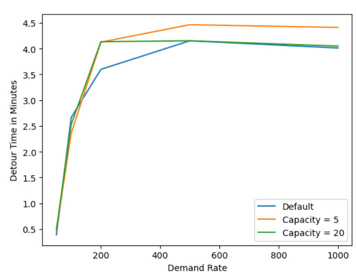


(e) Occupancy Rate over Demand Rate

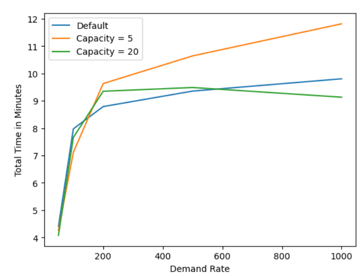
Figure 17: KPIs for different fleet sizes



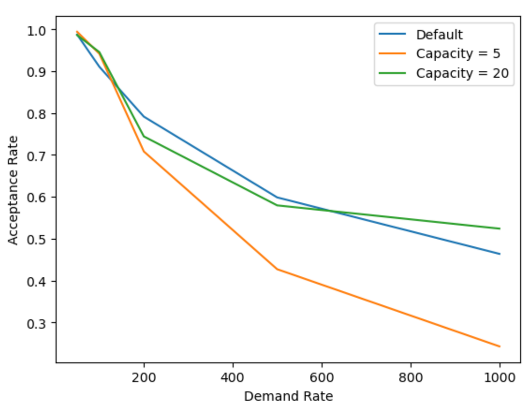
(a) Waiting Time over Demand Rate



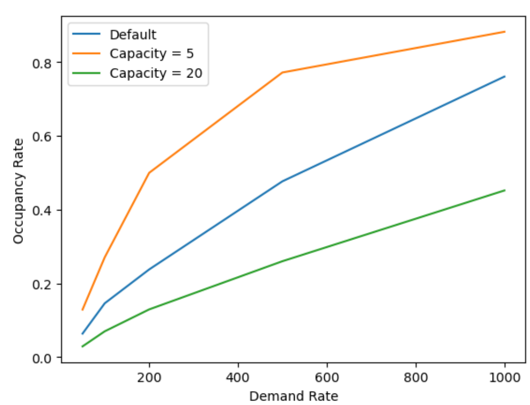
(b) Detour Time over Demand Rate



(c) Total Time over Demand Rate

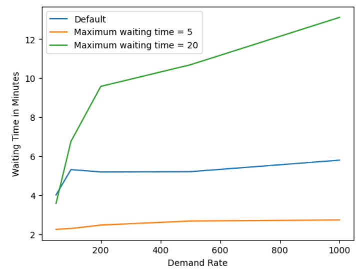


(d) Acceptance Rate over Demand Rate

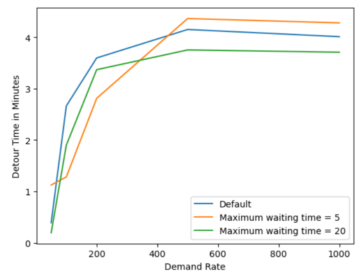


(e) Occupancy Rate over Demand Rate

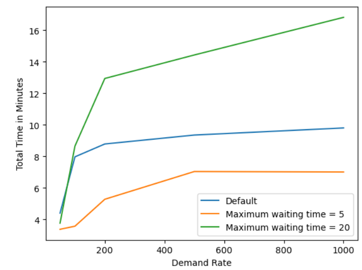
Figure 18: KPIs for different capacities



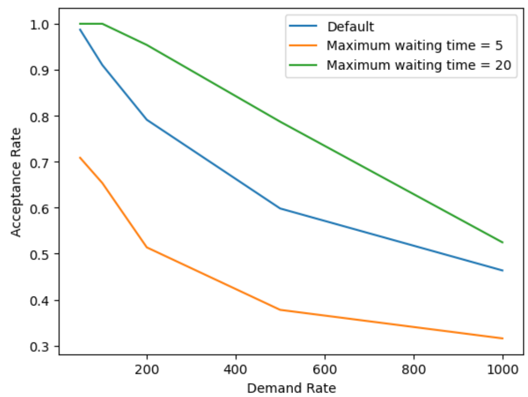
(a) Waiting Time over Demand Rate



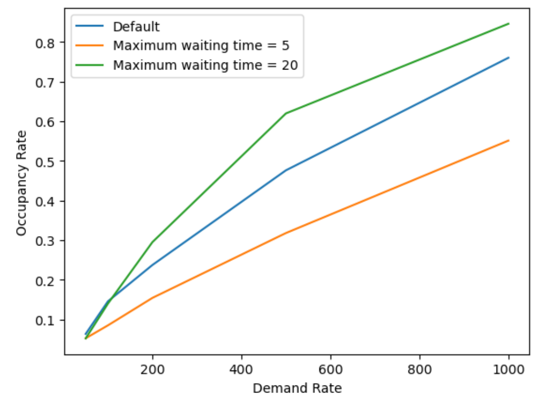
(b) Detour Time over Demand Rate



(c) Total Time over Demand Rate

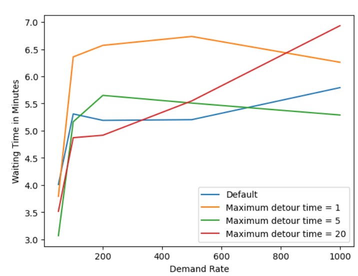


(d) Acceptance Rate over Demand Rate

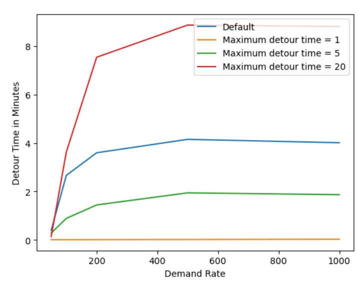


(e) Occupancy Rate over Demand Rate

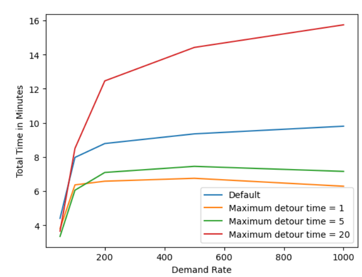
Figure 19: KPIs for different maximum waiting times



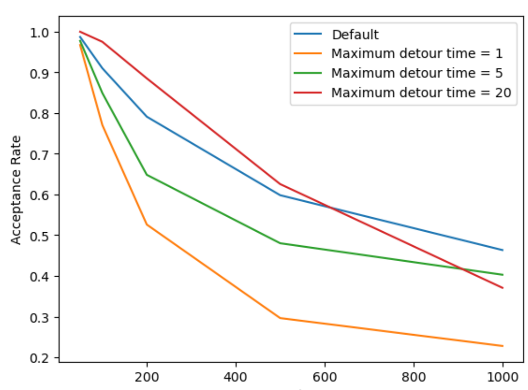
(a) Waiting Time over Demand Rate



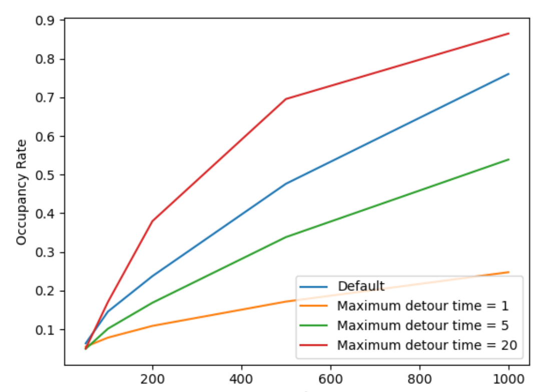
(b) Detour Time over Demand Rate



(c) Total Time over Demand Rate

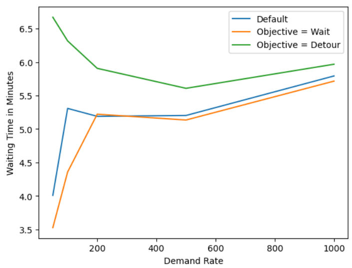


(d) Acceptance Rate over Demand Rate

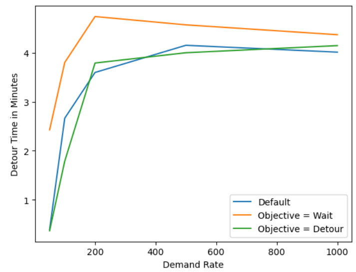


(e) Occupancy Rate over Demand Rate

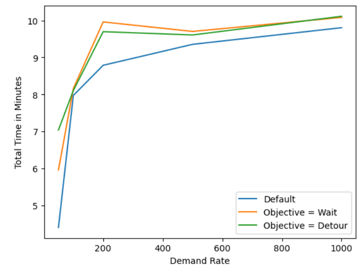
Figure 20: KPIs for different maximum detour times



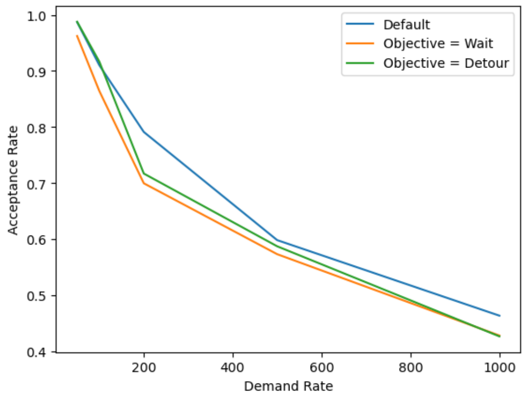
(a) Waiting Time over Demand Rate



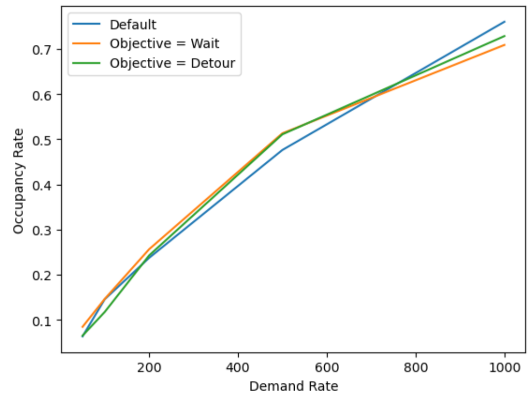
(b) Detour Time over Demand Rate



(c) Total Time over Demand Rate



(d) Acceptance Rate over Demand Rate



(e) Occupancy Rate over Demand Rate

Figure 21: KPIs for different optimization objectives

4.5 Bus Simulation

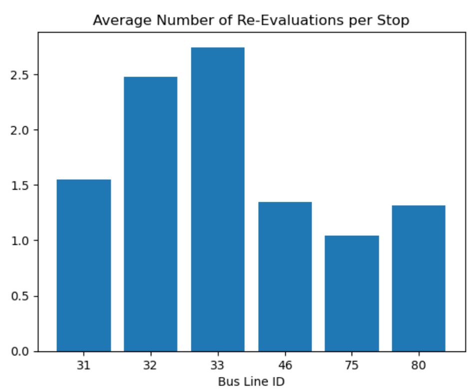
The simulation is constructed closely to the micro-transit simulation to ensure compatibility when combining the simulations. Similar to the On-Demand Micro-Transit simulation, the simulation starts with the initialization of the different components. For simplicity, it is assumed that the origin and destination of the requests – while still being uniformly distributed, can be served by one bus line. This avoids the additional complexity of implementing bus transfers. The buses leave the first stop of each line staggered with an equal headway.
When a new request comes in, the request is processed, i.e. it is determined which bus lines and which directions can be taken to get to the destination. Afterwards, the next request is generated.
When a vehicle, i.e. bus, arrives a station, its attributes get updated, e.g. current position and occupancy, route, and arrival times. Arriving passengers are dropped off. Lastly, waiting passengers get picked up if the buses route contains their destination and there is enough capacity.

5 Results for the Different Scenarios and Discussion

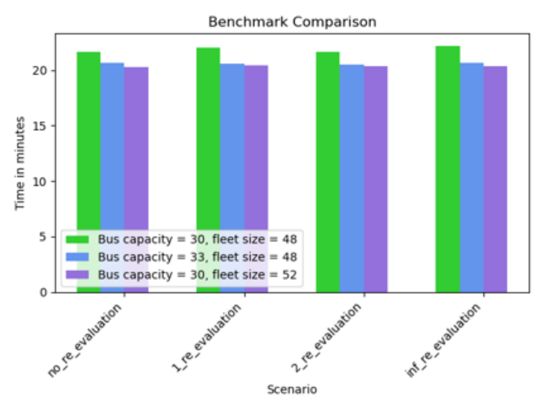
In this section the results of different scenarios tested on the on demand bus integrated simulation are shown and compared to a benchmark in order to evaluate in which cases the microtransit helps the network and enhances the KPIs. For each scenarios different parameters listed in the section 'Inputs' are varied. All the scenarios in this sections have a service rate of 100%. A disctict scenario where the service rate varies can be found in the annex.

5.1 Benchmark

The benchmark for comparing the results of the on-demand bus integrated system comprised a bus-only network with enhanced capacity, ensuring that its total capacity matched the combined capacity of the cabs and buses in the integrated system. Different ways to increase the capacity were tested, increase the fleet size of the buses or to increase the capacity of each bus by a little. For the first strategy 4 more buses a total of 120 seats were added to the system, one more for each of the most busy lines. The most busy lines are shown in figure 22a as the lines where most re-evaluations per stop happen. The number of re-evaluations refers to the number of times when the bus is at capacity a comparison between the microtransit travel time and next bus travel time are made at a stop for a specific passenger in order to assign it to the best service. More re-evaluations mean than the passenger was waiting for multiple buses/microtransit vehicle before one was available and had enough capacity.
In order to choose the strategy, average waiting time was plotted in figure 22b for varying numbers of re-evaluation strategies. The green line corresponds to the initial number of buses before the increase of capacity as a benchmark. The scenario where the bus fleet increased shows better results for all the varying re-evaluation scenarios, so is the one we keep as a benchmark network for the rest of the results.



(a) Average number of reevaluations per stop for the different lines



(b) Different benchmark strategies and their average delay in minutes

5.2 Re-evaluations

For the first scenario the number of re-evaluations is varied. The number of re-evaluations corresponds to the number of times when the bus is at capacity the comparison between choosing microtransit and the next bus to serves is made for a request waiting at a stop. With infinite re-evaluations this comparison is made every time until a request is assigned, whereas with no re-evaluations the request is assigned to the next bus with available capacity. For the other variants the comparison is made a few times and then if the request is not assigned yet it eventually gets assigned to the next available bus. The figures below illustrate some KPI measures. In the figure 23 we have the average waiting time and total travel time for the overall system. The green corresponds to the benchmark, the only bus network wit increased capacity. The scenarios that present the best results are the one with infinite re-evaluations and 2 re-evaluations. In figure **??** the average metrics for the microtransit vehicles(hatched and pale) and the buses. For the infinite re-evaluation scenario the average waiting time for the microtransit vehicles is significantly increased meaning that the microtransit vehicles take up the worst, most delayed requests. These request also seem to have the highest detour. As for the percentage of requests using the microtransit (figure **??**) the percentage keeps staying low due to the small capacity of the microtransit service compared to the buses, but it increases with the number of re-evaluations.

In order to have a good compromise between the average KPIs for buses and microtransit vehicles with no much change of the overall KPIs (and also in order to decrease computational efforts) we decide that the 2 re-evaluation scenario is the best to keep.

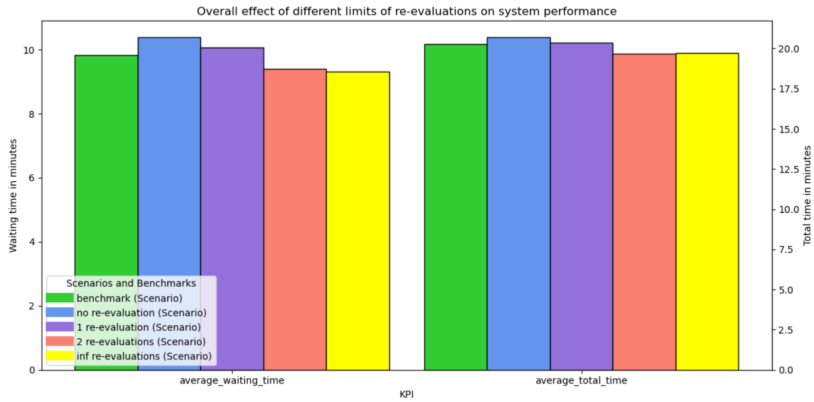
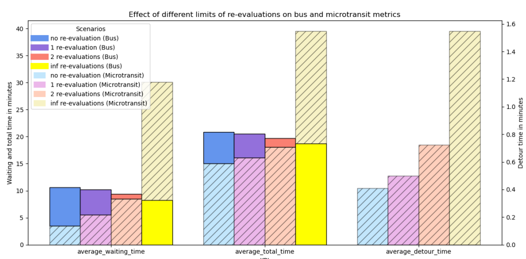
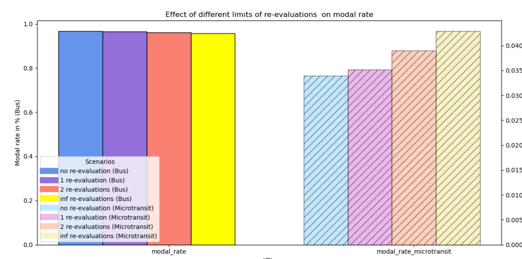


Figure 23: Overall effect of different limits of re-evaluations on system performance



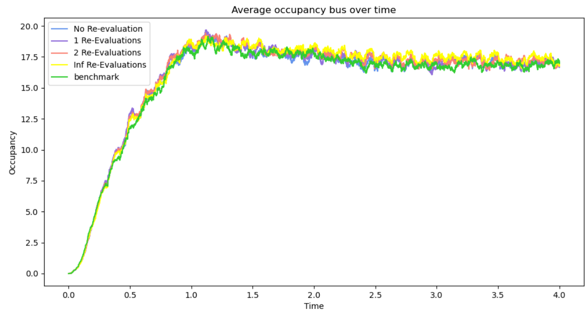
(a) Effect of different limits of re-evaluations on bus and microtransit metrics



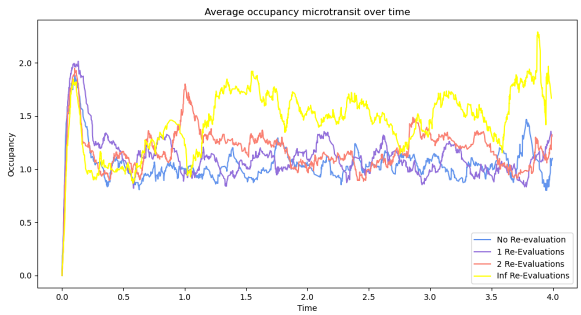
(b) Effect of different limits of re-evaluations on modal rate

Figure 24: Effect of different limits of re-evaluations on bus and microtransit KPI

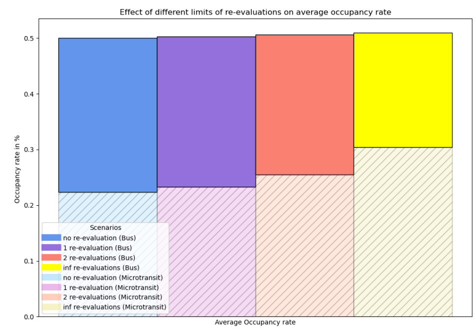
The figures below illustrate some occupancy metrics. In general we can see that buses are a bit more occupied compared to microtransit vehicles. But as the re-evaluation limit increases the occupancy of the cabs also increases. As for the occupancy over time it seems to be stable for both buses and cabs after the warm up period of 0.5-1 hours. For the buses their occupancy over time is slightly higher for the infinite re-evaluations and 2 re-evaluations compared to the benchmark scenario.



(a) Average bus occupancy over time for different limits of re-evaluations



(b) Average occupancy of microtransit vehicles over time for different re-evaluation limits



(c) Effect of different limits of re-evaluations on average occupancy rate

Figure 25: Occupancy metrics for microtransit vehicles and buses

5.3 Morning and Evening Peak Hours

In this section the scenarios have non-uniform demand and simulation is run over 5 hours. The scenarios in figure 27a have spatially dependent demand. Specifically, we have separated the nodes into the 'center' nodes and the 'outskirt'(suburb) nodes considering the Zurich network analysis, as illustrated in the figure 9b, the center ones being the ones inside the pink perimeter. For the morning peak scenarios the demand is double on the outskirt nodes and the destinations of the requests are towards the center nodes. For the evening scenario the opposite happens, the demand is the double on the center nodes and the destinations of the requests are towards the outskirt nodes. The other scenarios on the figure 27b (morning and evening peak with rise) have also the same spatial dependent demand but a temporal dependency is added. For the first 2 hours of simulation the number of requests per hour is lower and the between hours 2 and 4 the number of request per hour doubles. It finally drops again for the final hour. All the simulations are run with a limit of 2 re-evaluations and the reference scenario corresponds to the uniform demand scenario. It has to be noted that the total requests generated over the 5 hours is the same for both the spatial dependent and the spatial+time dependent scenarios and also equal to the total demand generated over 4 hours of the reference scenario. The time depedency is represented in figure 26.

In the figures below 27 the average overall KPIs are illustrated. The shaded color bars correspond to the benchmark scenario (only bus network) values run with the same demand configurations. It can be observed that for the morning peak scenarios the total travel time is just slightly better for the microtransit bus integrated simulation even if the waiting time is slightly higher. As for the evening scenario, when there is only spatial dependency the bus only network performs a bit better, whereas when there is also time dependency the microtransit bus network is better. In figure 28a we can see the KPIs for just the bus vehicles and microtransit ones. the highest detours and waiting and travel times happen during evening scenarios. For these scenarios the bus average waiting time is significantly higher than the reference scenario. For the morning scenarios the values for waiting time for the buses are similar to the reference benchmark. Finally, concerning the modal rate as illustrated in the figure 28b, for the evening scenarios it is higher for the cabs compared to the previous scenarios.

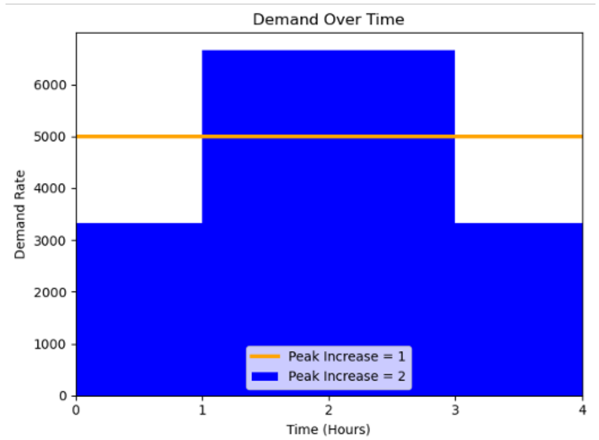
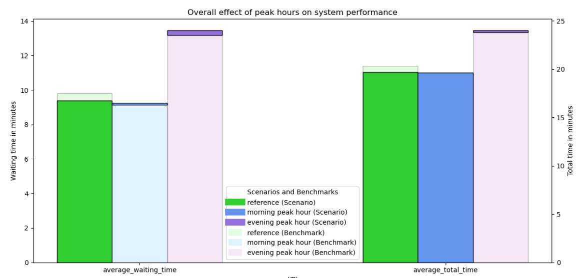


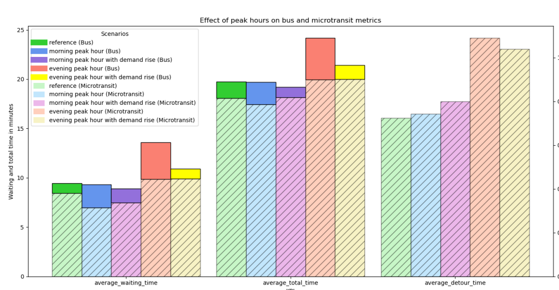
Figure 26: Time Dependency



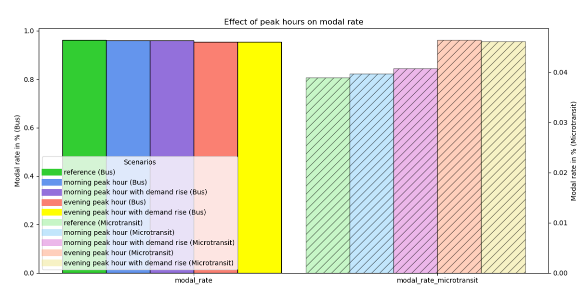
(a) Spatial dependency

(b) Spatial+Time dependency

Figure 27: Overall effect of peak hours on system performance



(a) Effect of peak hours on bus and microtransit metrics

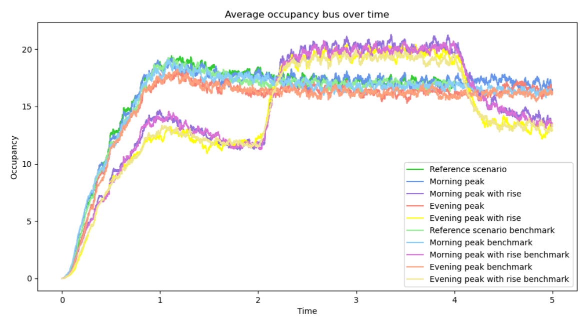


(b) Effect of peak hours on modal rate

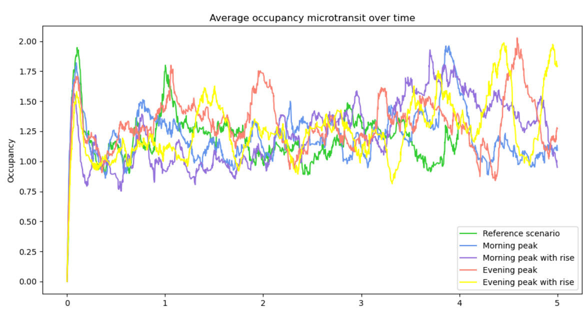
Figure 28: Effect of peak hours on bus and microtransit KPI

It can be assumed that since for the evening scenarios the origins are more closer to each other the matching for the microtransit vehicles is better and more requests can be served by the same vehicle, that can be the reason why the waiting time is relatively low compared to the bus waiting time and the detour high. On the other hand for the morning scenarios since the origins are more distributed less requests can be served by the microtransit. Additionally since the buses have their terminus on the outskirt nodes the passengers during morning scenarios can be picked up more easily by the buses, whereas for evening scenarios more buses might be full around the center nodes resulting in these higher waiting times.

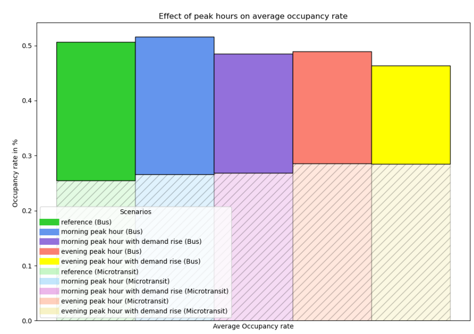
In the figures below occupancy metrics are plotted. For the bus vehicles (29a) for the time dependent scenarios there is a big increase in occupancy when the demand rise happen, the occupancy being even higher than for the reference scenario. As for the microtransit vehicles the occupancy presents fluctuations between 1 and 2 passengers, the occupancy rate being higher for the evening scenarios. For the evening scenario with rise where the microtransit and bus integrated system performs the best the bus occupancy is the lowest compared to the other scenarios.



(a) Average bus occupancy over time for different demand scenarios



(b) Average microtransit vehicle occupancy over time for different demand scenarios



(c) Effect of peak hours on average occupancy rate

Figure 29: Occupancy metrics for microtransit vehicles and buses

5.4 Congestion

In this section scenarios with congestion are tested. In order to simulate congestion an additional value taken from a distribution, a delay, is added at the bus route each time a bus reaches a stop. The delay distribution is generated using an average total delay 0.44 minutes and standard deviation 1.27 minutes and only positive numbers are considered. These values were the aggregated delay measures computed from the Zurich network.
Concerning the microtransit vehicles instead of a random delay taken from a distribution being added, a constant delay value is added to the internode times, during the congested period.
All the simulations are run over 5 hours and the congested period when there is stochasticity added to both microtransit and bus times happens between hours 2 and 4. The reference scenario is the one with uniform demand and no stochasticity in times and all the scenario including this are run with a limit of 2 re-evaluations. The following scenarios can be found in the figures below: the reference scenario in gree, one scenario when the microtransit has a constant internode delay of 0.5min, another when the microtransit delay value is 1min, and finally morning and evening peak scenarios with spatial dependency only and congestion (1min for the

microtransit). It has to be noted that in the scenario where the constant delays are 1 min for the microtransit vehicles, it is considered that the buses have dedicated lines that is why the microtransit has a higher delay. In the figure below 30 the different scenarios are compared to the bus network benchmarks (pale). The microtransit and bus integrated network performs overall a little bit better in terms of waiting time and travel time for the evening peak scenario and for both scenarios with congestion. Only the morning peak scanario is better with the bus only network. As for the microtransit and bus metrics (31a), the detour increases a lot with higher microtransit delay and is the highest for the evening scenario. In terms of total travel time the only time the bus performs better is when the delay for the microtransit is higher for the uniform demand scenario. For both evening and morning peak scenarios the waiting times for the microtransit vehicles is significantly lower than the one of the buses. As for the modal rate of the microtransit(31b) the highest is for the evening and morning scenarios and the scenario where the delay of the microtransit is around the same as the one of the bus.

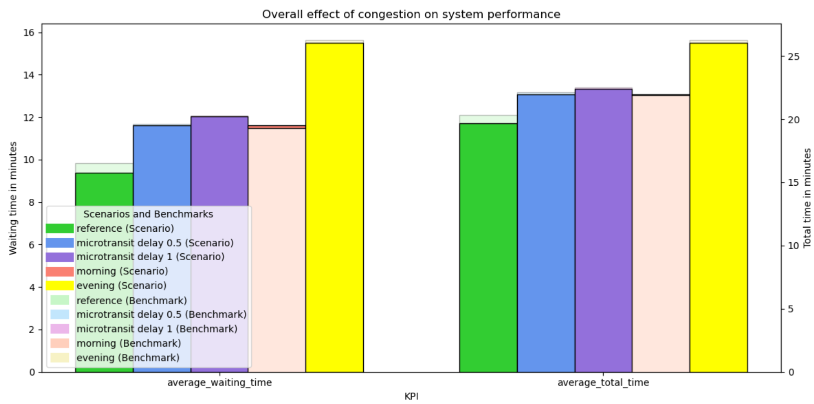
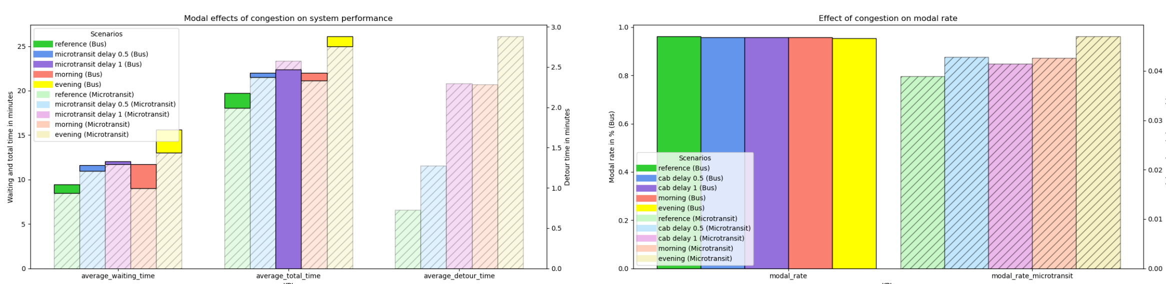


Figure 30: Overall effect of congestion on system performance



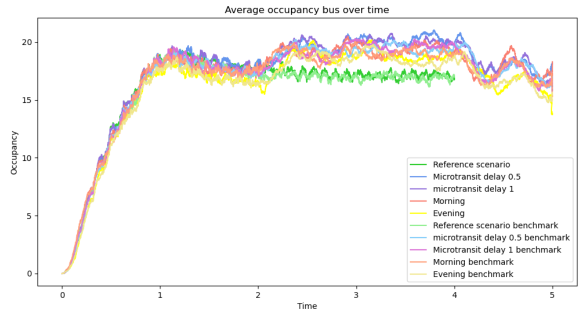
(a) Effect of congestion of bus and microtransit metrics

(b) Effect of congestion on modal rate

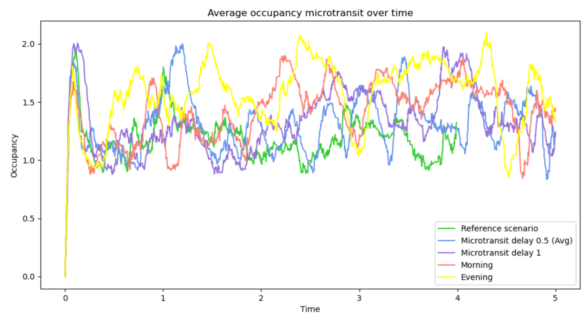
Figure 31: Effect of congestion on bus and microtransit KPI

It can be concluded than the microtransit service helps overall the bus system during congestion especially for the uniform and evening peak scenario and in general the passengers that are picked with microtransit have a better level of service.

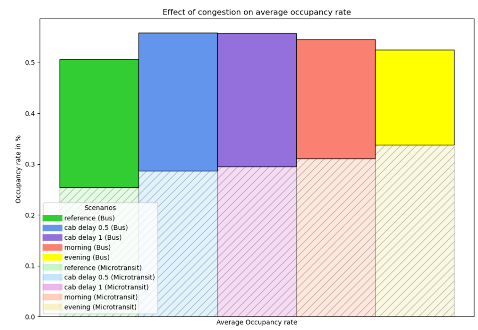
On the figures below bus and microtransit occupancy metrics are illustrated. During congestion period the bus occupancy increases a bit and is higher than the reference scenario but then drops again at the end of congestion (32a). For the microtransit vehicles the occupancy rate is the highest for the evening peak scenario and even the average occupancy over time for this scenario is relatively high. Compared to the reference scenario all the microtransit vehicles are more occupied over time .



(a) Average bus occupancy over time for different congestion scenarios



(b) Average microtransit vehicle occupancy over time for different congestion scenarios



(c) Effect of congestion on average occupancy rate

Figure 32: Occupancy metrics for microtransit vehicles and buses

6 Results for Increased Microtransit Capacity

In the previous simulations, microtransit increased the total network capacity by 8.3 %. To see the impact of a more significant capacity increase, a few scenarios where the capacity was increased by 20.8 % by microtransit were simulated. For these scenarios, two alternatives were implemented:

1. The capacity of the microtransit vehicles (cabacity) is increased from 4 to 10, now representing small buses.
2. The fleet size of microtransit vehicles is increased from 30 to 75 while maintaining the capacity of 4.

Both strategy add the capacity, that is seats, to the bus network. The two strategies were run for the "2 re-evaluation" scenario and compared to the one of the previous simulations and their corresponding only bus networks.

6.1 Benchmark

Similar to the previous simulations, multiple benchmark scenarios were examined (figure 37b). The status quo is the existing bus network without microtransit service. To match the capacity of the microtransit vehicles, the bus fleet size was increased to 58 in one scenario, and the bus capacity was increased to 36 in the other. Again, the increased fleet size results are the best.

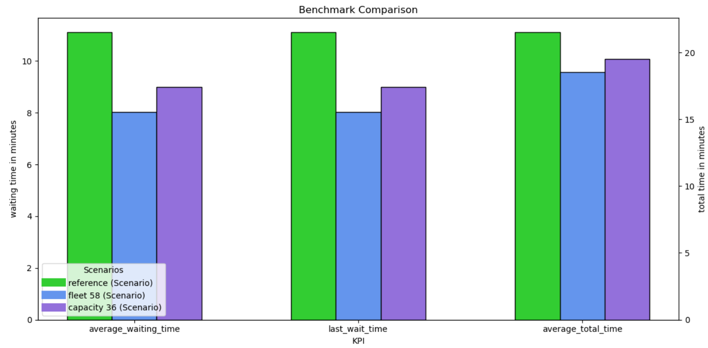


Figure 33: Benchmark Comparison

Compared to the previous benchmarks (here: OLD), the benchmarks for the higher capacities (here: NEW) show better results (figure 37). The small difference in the status quo can only be explained by the randomness of the simulation.

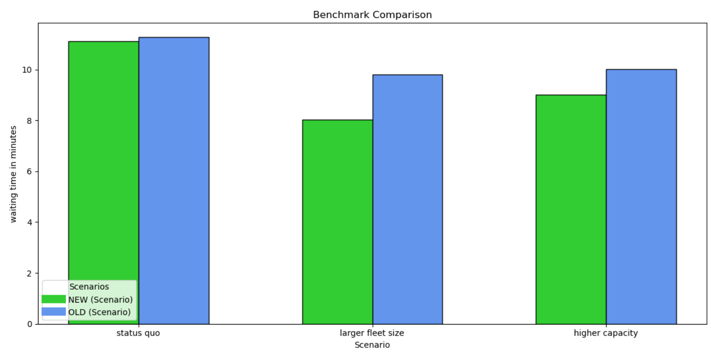


Figure 34: Benchmark

6.2 Results

The results of the two new strategies are plotted and are compared to the new benchmark. The reference scenario corresponds to the original 2 re-evaluation scenario without the increased microtransit capacity. We can observe on figure 35 that for both scenarios, the hybrid microtransit-bus system performs significantly better than the bus benchmark. Compared to the reference scenario, the waiting and total times are almost halved. The difference between the benchmark and hybrid system performance is more pronounced than for the reference scenario. Both new scenarios show similar overall metrics.

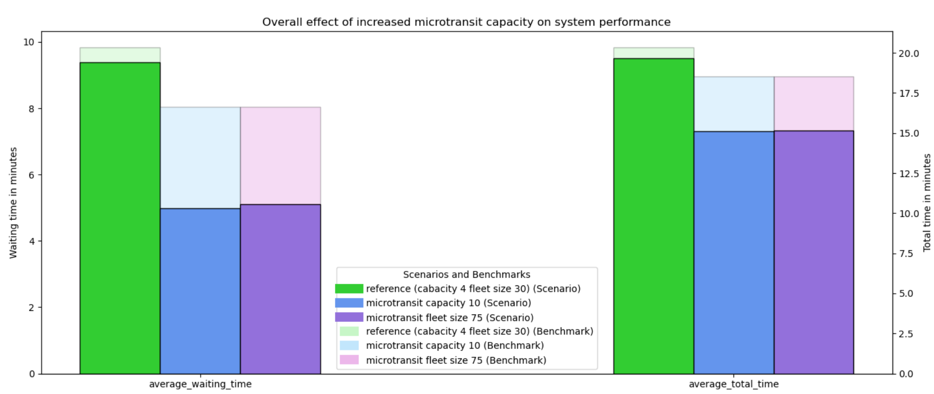
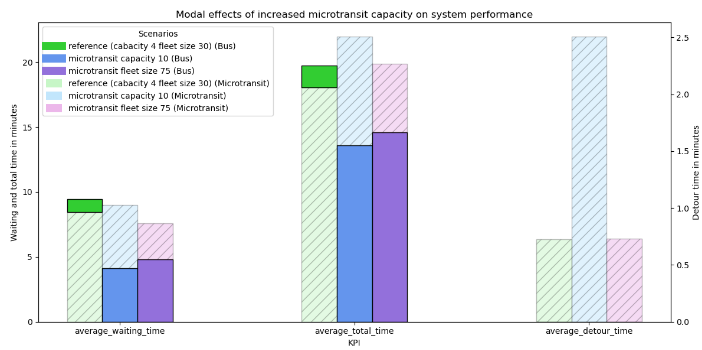
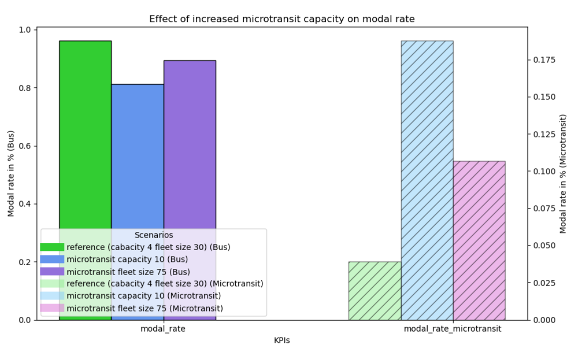


Figure 35: Overall effect of increased microtransit capacity on system performance

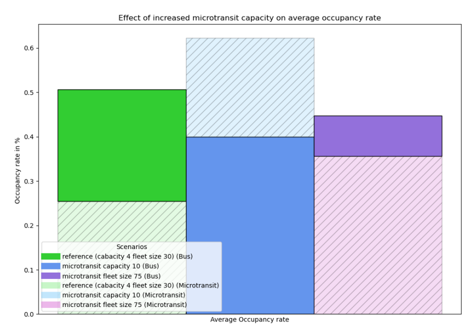
Concerning the modal split, passengers traveling by bus have overall lower average waiting and total times for the increased capacity scenarios, unlike the reference scenario. The detour is similar when the microtransit vehicle capacity is equal. For the increased microtransit vehicle capacity, the average detour time is much higher. As expected, detour time increases as more passengers travel in one vehicle. However, the average detour time makes up less than 12 % of the average total case in any case. The microtransit services has a higher modal share in the increased capacity scenarios. As a consequence, occuapncy rates are higher for microtransit vehicles and lower for buses. When the microtransit vehicles have more seats, the occupancy is higher reaching 6 passengers in the microtransit vehicle. For the increased fleet size scenario, the occupancy rate is not as significant but still higher than for the reference scenario. Finally the modal share of microtransit reaches 17.5% in the case of increased vehicle capacity and 10% for the case of increased fleet. This can be seen in figures 36b and 36c as well.



(a) Effect of increased microtransit capacity of bus and microtransit metrics



(b) Effect of increased microtransit capacity on modal rate



(c) Effect of increased microtransit capacity on occupacny rate

Figure 36: Effect of increased microtransit capacity on bus and microtransit KPI

It can be deducted that microtransit services can significantly benefit the overall system performance if the additional capacity is large enough. Both scenarios, that is, increased vehicle capacity and increased fleet size, have similar average waiting and total times. The difference can be explained by randomness of the simulation. However, added congestion is not considered in these scenarios. Increasing the vehicle capacity is likely the better option, as it adds less vehicles to the already congested road network. Increasing the fleet size would lead to hundreds of addtional vehicles for the whole Zurich bus network. In addition, less drivers are needed if only the vehicle capacity is increased. This can be an important factor with the existing driver shortage and can keep the variable costs lower.

In conclusion, the increased microtransit capacity for both scenarios improves the system a lot overall. For the increased vehicle capacity scenario, even though the metrics of microtransit users are up to 5 minutes higher than the ones of bus users, the vehicle occupancy and the modal share of microtransit are significantly improved. As for the increased fleet scenario, the metrics stay in a similar range to the reference, but the modal share is increased. Considering the impact on congestion and workforce needs, increasing the vehicle capacity is likely the best option.

7 Conclusion

Several scenarios were analyzed to test the simulation and to determine when and how it can be beneficial to introduce on-demand microtransit service to a bus network. Coming back to the research questions, various insights were found. The research questions were as follows:

1. Can complementary flexible schedule microtransit service assist in improving service quality and performance of fix schedule buses?
2. How can proper coordination between the two services be ensured?

7.1 Effect of On-Demand Microtransit Service Implementation

The microtransit-bus hybrid system generally performs better than the bus-only network in various scenarios. The hybrid system performs particularly well during congestion and evening peak hours, where it reduces overall waiting and travel times compared to the bus-only benchmark. In scenarios with non-uniform demand, the hybrid system shows better performance during evening peaks, especially when there is a temporal dependency in demand. The hybrid system's performance is further enhanced when microtransit capacity is increased, either through larger vehicle capacity or increased fleet size. These improvements lead to significantly reduced overall waiting times and total travel times, sometimes nearly halving them compared to the reference scenario. Considering the additional congestion and workforce needs when increasing the microtransit fleet size, increasing the vehicle capacity is the better solution. Overall, the microtransit service complements the bus system effectively. The optimal microtransit capacity compared to bus capacity needs to be determined with additional test and real world applications. However, it was shown that adding an on-demand microtransit service with approximately 20 % of the bus seat capacity to the network can have a major positive effect on waiting and travel times.

7.2 Efficient and proper coordination

An efficient and proper coordination between the two services is crucial to maximize system performance and serviceability. Microtransit arrival time estimations were an efficient method to reduce computational effort, average waiting and total times. Both services showed promising KPI. Continuously adapting the estimation based on real world data could further improve the efficiency after the implementation.

7.3 Future Outlook

7.3.1 OD-Matrix

No data was found for real origin-destination data. Therefore, the OD matrix was assumed to be random and within one bus line. That is, the origin was randomly selected out of all stops, and the destination was chosen so that it can be reached with one single bus line. An improvement that can be made is to have more realistic origin-destination pairs by allowing bus transfers to the system and using real world data instead of randomness.

7.3.2 Microtransit Vehicle Relocation

Concerning the microtransit vehicles, for the scenarios of non-uniform spatial demand, it would potentially be beneficial to relocate the vehicles to the stops where the demand is concentrated when they are idle.

7.3.3 Different Assignment Strategies

It would be interesting to explore other assignment strategies, since the microtransit vehicles are mostly half occupied. An idea would be for the vehicles to wait a little bit more until they are full. Another strategy could be to focus on the direction where the demand is higher, e.g., into the city during the morning rush hours. Such strategy might improve the overall metrics.

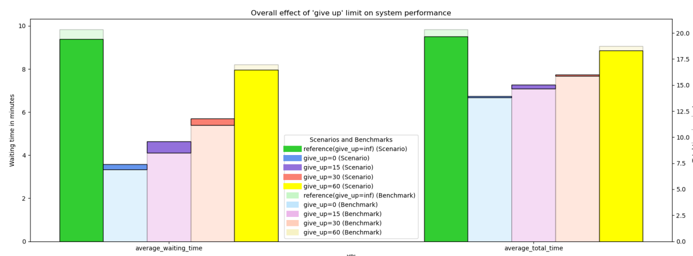
7.3.4 Matching Algorithms

The matching algorithms that were used in this project require a lot of computational effort. The greedy algorithm is an exact solution that finds the optimal solution. It would be interesting to explore other matching algorithms such as Hybrid Simulated Annealing or Heuristics. This could allow for real time solutions that could be introduced in existing bus networks. [2].

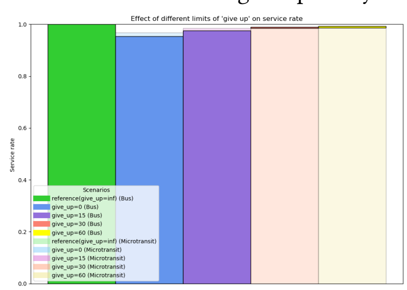
8 Appendix

8.1 Give up scenario

In this section a slightly different scenario is tried. This scenario cannot be compared with the other since the service rate is not up to 100. For this scenario we introduce a parameter called give up which is in minutes. At the moment when a bus arrives at capacity if the total waiting time since the generation of the request exceeds the give up limit then the request in not served. The different give up times tested were 0 minutes (meaning that the request 'gives up' immediately when the bus arrives at capacity, 15 minutes, 30 minutes and 60 minutes. In the figure below the give up scenarios are compared to the reference scenario where the give up is technically infinite time (the number of re-evaluations is 2 as the previous reference scenario).
As it can be observed on figure 37a the average waiting and total travel time decrease significantly as the give up limit decreases. At the same time the percentage of requests served decreases also with a lower give up limit (37b). The bus only network, the benchmark tends to perform better than the microtransit bus integrated network when the give up limit is up to 20 minutes. When the limit is set to 30 minutes even thought the bus only network presents better performance, the percentage of requests served is lower than the hybrid system.



(a) Overall effect of different limits of 'give up' on system performance

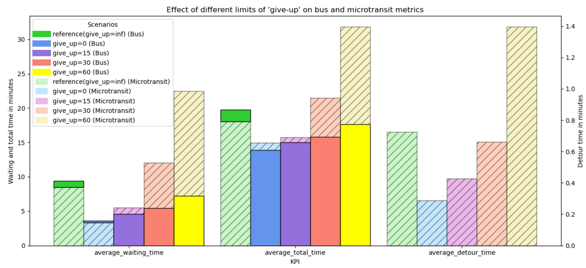


(b) Effect of different limits of 'give up' on service rate

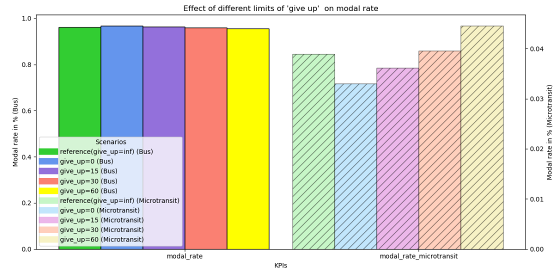
Figure 37: Overall effect of different limits of 'give up' on KPI

As for the bus and microtransit metrics, the bus metrics seem to be better for all the give up scenarios (38a). As the give up limit increases the average waiting time, total travel time and detour time rise a lot for the microtransit service, meaning that microtransit take up the worst requests that have to wait the longest. Additionally, when the give up limit is 30 and less the modal rate is lower than the reference scenario (38b) meaning that not a lot of requests are assigned to microtransit. Only for the scenario where the hybrid system performs better than the bus only network the modal rate of microtransit is rather high.

Finally, in terms of occupancy metrics, the buses seem to be less occupied over time when the give up limit is lower (39a). The microtansit vehicles also follow this trend and the average occupancy is higher the case when the give up limit is at 60.

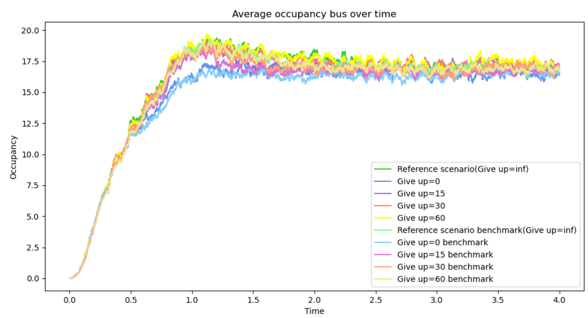


(a) Effect of different limits of 'give up' on bus and microtransit metrics

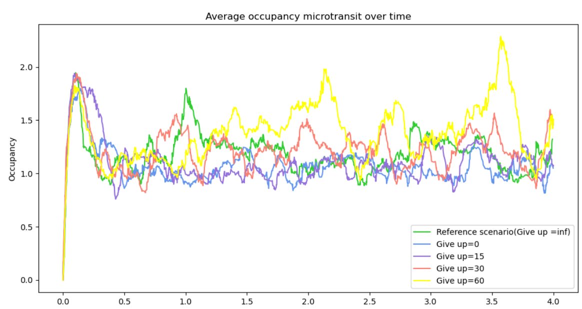


(b) Effect of different limits of 'give up' on modal rate

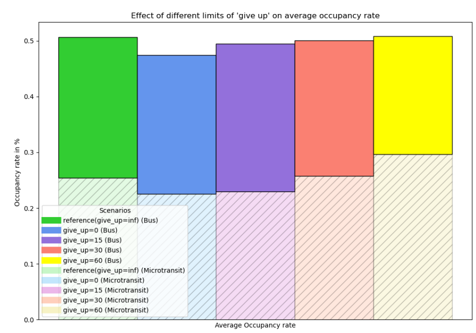
Figure 38: Effect of different limits of 'give up' on bus and microtransit KPI



(a) Average bus occupancy over time for different 'give up' limits



(b) Average microtransit vehicle occupancy over time for different 'give up' limits



(c) Effect of different limits of 'give up' on average occupancy rate

Figure 39: Occupancy metrics for microtransit vehicles and buses

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